Australian Government
National Water Commission

Integrated resource planning for urban water —resource papers

Institute for Sustainable Futures

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Waterlines

A SERIES OF WORKS COMMISSIONED BY THE NATIONAL WATER COMMISSION ON KEY WATER ISSUES

Waterlines

These papers are part of a series of works commissioned by the National Water Commission on key water issues. This work has been undertaken by the Institute for Sustainable Futures on behalf of the National Water Commission.

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Abbreviations and acronyms

ABS	Australian Bureau of Statistics
ACT	Australian Capital Territory
ANN	artificial neural network
ANOVA	analysis of variance
ARIMA	autoregressive integrated moving average
ARMA	autoregressive moving average
BASIX	Building Sustainability Index
BCC	Brisbane City Council
BoM	Bureau of Meteorology
BT	artificial neural networks
BWP	bulk water production
BWPD	bulk water production data
CBA	cost–benefit analysis
CEA	cost-effectiveness analysis
CMD	customer metered demand
CMDD	customer meter demand data
CO_2	carbon dioxide
CPRS	Carbon Pollution Reduction Scheme
CSIRO	Commonwealth Scientific and Industrial Research Organisation
DALY	disability-adjusted life year
DAN2	Dynamic artificial neural network (model)
DCLG	Department of Communities and Local Government (United Kingdom)
DEUS	Department of Energy, Utilities and Sustainability (NSW)
DFT	dual-flush toilet
DSM DSS	demand-side management decision support system
EBMUD	East Bay Municipal Utility District (California)
ENSO	El Niño – Southern Oscillation
FFBP	feedforward backpropagation
GCM	global climate model
GHG	greenhouse gas
GIS	geographic information system
GLM	general linear model
GS	Garden Smart
IAP2	International Association for Public Participation Australasia
IPART	Independent Pricing and Regulatory Tribunal (NSW)

IPCC	Intergovernmental Panel on Climate Change
IPO	Interdecadal Pacific Oscillation
IRP	integrated resource planning
iSDP	integrated supply–demand planning
ISF	Institute for Sustainable Futures
IWCM	integrated water cycle management
IWM	integrated water management
IWR–MAIN	Institute for Water Resources—Municipal And Industrial Needs
LCD	litres per capita per day
LUDs	land use unit demands
M&E	monitoring and evaluation
MCA	multi-criteria analysis
MD	maximum day
MDB	Murray–Darling Basin
MDMM	mean day maximum month
MPMC	matched pairs means comparison
NPV	net present value
NWC	National Water Commission
NWI	National Water Initiative
OLS	ordinary least squares
REC	renewable energy certificate
RWT	rainwater tank
SD	standard deviation
SE	standard error
SEQ	south-east Queensland
TEV	total economic value
UTS	University of Technology, Sydney
WELS	Water Efficiency Labelling and Standards
WSAA	Water Services Association of Australia
WSH	Water Smart Homes
WSUD	water sensitive urban design

Preamble

The Australian urban water industry faces significant challenges to meet growing demands on urban water resources under a shifting climate. To tackle these challenges, the sector must adopt new supply and demand strategies to enhance climate change resilience, improve water use efficiencies, and protect our urban waterways – all in a transparent and cost-effective manner.

The industry also needs to better understand community expectations regarding levels of service, manage the risks entailed in more sophisticated water supply systems, minimise greenhouse gas emissions, and develop the expertise required to achieve sustainability across the water, energy and land-use planning nexus.

Good-quality, robust and relevant information is needed to help the sector make decisions concerning these emerging challenges. In 2007 the National Water Commission, in partnership with Water Services Association of Australia (WSAA), identified several important areas where nationally coordinated action would benefit the Australian urban water sector and progress commitments made under the National Water Initiative and the COAG. Embarking on this project, the Commission and WSAA had several objectives in mind:

- build capacity and improve planning by urban water utilities by developing resources that support best practice urban water supply and demand planning

- create resources specifically targeting the water planning needs of regional and smaller urban water utilities and local councils, where resources and skills can often be in scarce supply

- provide resources that will assist the urban water utility sector and local government water managers to better incorporate community values and public benefits and as part of their water planning and investment decisions

- support water managers and utilities to start the complex task of incorporating climate change into water supply and demand planning.

The Integrated Resource Planning tools and resources that make up this package have been developed by industry, for industry, under the guidance of a steering committee comprising of urban water planners and practitioners from major and regional water utilities. The Commission and WSAA are pleased to offer the package of resources and tools as a contribution to assist the sector in meeting its future challenges.

Ross J Young

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Executive Director
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1. Introduction

This document is the compiled suite of resources developed as part of the Integrated Resource Planning for Urban Water project funded by the National Water Commission (NWC). It draws on the principles of integrated resource planning (IRP) and builds on a body of work previously undertaken for the Water Services Association of Australia (WSAA).

This chapter provides a brief introduction to IRP, the Integrated Resource Planning for Urban Water project and the previous work.

1.1 Integrated resource planning

IRP is a process of planning services in a way that ensures the efficient and sustainable management of water, energy or other resources. It involves considering both the projected demand and the available supply to determine the supply–demand gap. It also involves considering a suite of options with the potential to reduce demand or increase supply. Demand management and water/energy/resource conservation are core to IRP. Developed by the electricity industry in the United States in the 1980s, IRP has been applied to the planning of other large infrastructure systems, and has become an important component of water supply planning in Australia since the early 1990s.

Vickers (2001) describes IRP as an open, participatory, strategic planning process, emphasising least-cost analysis of options for meeting service needs, while for Swisher (1997) IRP is a planning process that aims to integrate centralised and distributed sources of supply; conservation measures and supply-side options; and often-conflicting economic, social and environmental objectives. IRP generally involves making detailed forecasts of demand, developing a wide range of options, assessing demand- and supply-side options on an equal basis, and deciding how to meet objectives at least cost while accounting for sustainability impacts and uncertainties.

While supply–demand questions remain a core area for the application of IRP in all situations, a key feature of IRP's application to urban water is that it can consider wastewater objectives as well as water supply objectives. Another feature is that impacts across the total water cycle will be relevant. IRP for urban water can be characterised as planning for water services in a way that values water conservation as much as it values augmenting existing water supply, wastewater and stormwater systems.

IRP is only one framework within the broad field of integrated urban water management. It has both similarities to and differences from other frameworks, approaches and tools in the field, such as integrated water cycle management (IWCM), integrated water management, water sensitive urban design (WSUD) and Water Sensitive Cities. These approaches focus on the integration of water supply, wastewater and stormwater systems and the integration of land and water management on a catchment basis. IRP for urban water also addresses those issues but retains a focus on the integration of water conservation with supply augmentation.

1.2 The Integrated Resource Planning for Urban Water project

The Integrated Resource Planning for Urban Water project, led by the Institute for Sustainable Futures at the University of Technology, Sydney, involved collaboration with WSAA, the Commonwealth Scientific and Industrial Research Organisation (CSIRO), Brisbane City

Council, Riverina Water County Council and Wagga Wagga City Council, as well as the NWC.

The project comprises a series of resource papers on various topics, two case studies and further development of an existing demand forecasting and options model called the Integrated Supply–Demand Planning (iSDP) model. The project also updates the existing *Guide to demand management* (Turner et al. 2008) and demand-management training package developed by the Institute for Sustainable Futures for WSAA members. The updated guide is titled *Guide to demand management and integrated resource planning for urban water*.

The resource papers are intended to inform a national water industry audience and specifically to assist those involved in urban water planning to deal with emerging issues in supply–demand planning. The resource papers cover:

- Sustainability assessment in urban water IRP (Chapter 2)
- Complementary analytical techniques for urban water forecasting in IRP (Chapter 3)
- Incorporating climate change into urban water IRP (Chapter 4)
- Techniques for estimating water saved through demand management and restrictions (Chapter 5).

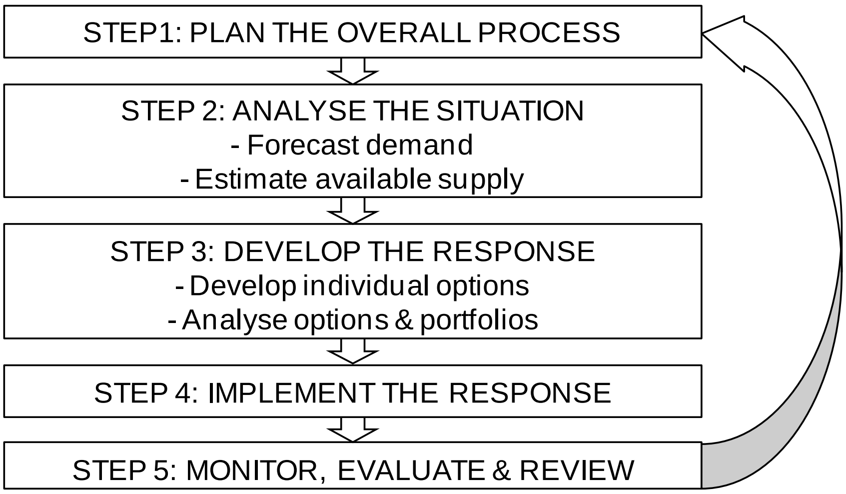
The first three of these papers were developed through a three-stage process. First, a scoping paper was drafted, based upon current literature. The scoping paper was then used to brief key practitioners from around Australia, who were invited to a series of industry workshops on the field and brought together for facilitated discussion. The workshop discussions were used to shape the development of a draft resource paper on each subject. All the resource papers were reviewed by a technical working group comprising Australian water industry representatives.

For more details on the NWC Integrated Resource Planning for Urban Water project, go to *http://urbanwaterirp.net.au*.

1.3 The Australian IRP framework

The *Guide to demand management and integrated resource planning for urban water* and associated materials developed for WSAA, such as the iSDP model and training materials (updated as part of this project), are based on the Australian IRP framework. The existing IRP framework has also been used as a point of reference for this document. The framework for urban water planning has five major steps (see Figure 1.1).

Figure 1.1: The main steps in the Australian IRP framework



Source: Turner et al*. (2010).*

Step 1 covers planning the overall process. It involves initial problem framing and establishing the process. Step 2 (Analyse the situation) includes water demand forecasting and assessing available system yields. Step 3 (Develop the response) covers the development and analysis of demand- and supply-side options, the selection of options and the development of portfolios of options. Step 4 (Implement the response) involves implementing the portfolio of options determined in Step 3. Step 5 (Monitoring, evaluation and review) covers the evaluation of outcomes for both the implemented response and the overall process.

1.4 References

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Vickers A (2001). Handbook of water use and conservation, Waterplow Press, Amherst, Massachusetts.

2. Sustainability assessment in urban water IRP

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Summary

What is the purpose this paper?

The purpose of this paper is to provide urban water planners with the background required to make informed decisions about how they will incorporate sustainability impacts into options assessments. The paper focuses on options used in integrated resource planning (IRP) for supply–demand planning. It will be of interest to those considering multi-criteria analysis (MCA), such as that documented in the WSAA sustainability framework (Lundie et al. 2008a), 'triple bottom line' assessment or valuing sustainability impacts in dollar terms as 'externalities'.

This paper should provide readers with the information needed to:

- decide which approach will best suit their situation
- identify what the implications of selecting a particular approach are likely to be
- decide what will be needed for the assessment to constitute good practice in sustainability assessment.

The paper aims to inform the reader about the implications of different approaches and how to use other resources on MCA and externality valuation together with the Australian IRP framework (see Chapter 1 for an overview of the IRP framework).

The paper does not aim to provide a step-by-step guide for conducting a sustainability assessment.

Why is the paper needed?

Despite the widespread recognition of the importance of sustainability assessment, there is a lack of guidance for urban water planners on how to choose between the different decision-making frameworks available for incorporating sustainability. The WSAA sustainability framework, documented in Lundie et al. (2008a), guides readers on the use of MCA. It is drawn on extensively in this paper. There is less information available on how to value the sustainability impacts of urban water systems in dollar terms as externalities for inclusion in urban water planning. Before this paper, there has been limited guidance that directly compares the different decision-making frameworks and highlights the advantages and challenges of each.

Will this paper be useful to me?

The primary intended audience for this paper is urban water planners working at the scale of a single utility's area of operations or planning for a particular water system or sub-area. It should be useful to those tasked with developing regional urban water supply–demand or

integrated water cycle management (IWCM) plans. However, the question of how best to include sustainability impacts together with direct costs in the assessment of options for urban water is equally relevant to those engaged in studies of IWCM for a new suburb or development site.

What are the approaches to sustainable assessment for urban water and how do they compare?

This paper compares approaches that utilise multiple criteria to assess sustainability impacts to economic evaluation methods for assessing those impacts as externalities using the single criterion of dollars.

In relation to economic evaluation, the paper focuses on including externalities into an extended cost-effectiveness analysis (CEA) rather than a cost–benefit analysis (CBA) because CEA is used within the existing IRP framework. In CEA, the objective (such as having a secure water supply for a region over a given planning period) is set, and potential options are considered to meet that objective. Despite the focus on CEA, the discussion of economic evaluation in the paper is equally applicable to CBA.

In many situations, treating sustainability impacts as externalities in an extended CEA or CBA is not viable, given the constraints of the available data for measuring and valuing 'externalities' and the resources available for generating additional data. Furthermore, the potential exists for impacts to be considered 'intangibles' in the economic sense. They cannot be valued adequately in dollars. In such situations, some form of MCA may well be the only approach available for including sustainability impacts.

MCA is not a 'quick and dirty' alternative to sustainability assessment. The requirements for good practice in MCA, particularly in relation to the participation of stakeholders, necessitate careful consideration and sufficient resourcing. How MCA integrates with the existing IRP framework also needs to be considered. Likewise, consideration should be given to how the results of assessments against different criteria will be aggregated. The outcome of an MCA can be a single 'score' for each option and a 'triple bottom line' scoring on economic, environmental and social indexes, or independent scores against each criterion for all options.

In Table 2.1 the principles of IRP as described by Vickers (2001) and Swisher et al. (1997) are used to contrast extending CEA via economic evaluation of externalities and MCA. It provides a summary of the comparisons between approaches that are made in this paper.

Table 2.1: Comparison of economic evaluation of externalities in extended CEA and MCA against IRP principles

IRP principle	*Extended CEA*	*MCA*
An open and transparent planning process	In CEA the objective is clear. Alternatives are considered in relation to how cost-effectively they meet the objective. There is a potential loss of transparency in extending CEA, both in how externalities are valued and through including direct costs with externalities in a single dollar value.	The potential for openness is seen as one of the key strengths of MCA because all the objectives and criteria are usually clearly stated. However, whether criteria overlap and result in a form of double counting is commonly less clear.
Participatory planning process	It is technically possible to include stakeholder values in an extended CEA in a robust way with no significant stakeholder participation. However, stakeholder participation is a highly effective means of identifying and mapping stakeholder groups, as well as mapping out which impacts exist.	Stakeholder participation is essential for good practice in MCA and advocates of MCA see the potential for stakeholder participation as a strength of the approach. Critics of MCA highlight the 'gaming' that can result from stakeholders selecting assessment criteria.
Emphasising least cost … for meeting service needs	A key advantage of extended CEA is that it retains a focus on minimising the cost of service provision.	Relative cost-effectiveness can easily be lost in MCA. It can then be difficult to demonstrate that the final portfolio of options selected to meet the goals and objectives of a water strategy do so cost-effectively. How MCA can be integrated with the existing IRP framework is addressed in this paper.
Integrating demand management with increased supplies	Emphasising least cost highlights that many demand-management options are low impact and highly cost-effective.	With MCA, highly cost-effective demand-management options may be missed if only options popular with stakeholders (such as reuse and rainwater tanks) are compared to large-scale supplies.
Integrating often conflicting economic, environmental and social objectives	There are inherent difficulties in measuring all economic, environmental and social values of sustainability impacts in dollar terms. The potential exists for impacts that will be considered 'intangibles'. For some impacts, there is unlikely to be the data required to make the links from the source of the externality through the changes in the biophysical environment to who is affected and to what extent.	MCA can be well suited to integrating multiple, often conflicting, objectives. Various MCA methodologies are designed to do just that. MCA can incorporate some impacts that cannot be valued adequately in dollar terms where the linkages are difficult to establish quantitatively. However, the extent to which the results of assessments against different criteria can sensibly be aggregated need to be considered.

When would each approach make sense?

Extending CEA via the economic evaluation of externalities makes sense where the ranking of options and portfolios of options in terms of relative dollar costs is the best means of communicating the choice involved to decision makers. While placing dollar values on some sustainability impacts can be problematic, it provides a critical relativity between impacts and direct costs and between choices among urban water options and other public policy goals. Extended CEA requires the availability of sufficient data that can both measure and value the significant sustainability impacts of options as externalities. Alternatively, resources will be needed to conduct the biophysical and valuation studies to collect that data.

MCA makes sense where it is recognised that decision-making may involve multiple objectives and multiple viewpoints, and that there will need to be trade-offs between objectives and viewpoints. MCA also makes sense where stakeholder participation is likely to be considered an important part of the sustainability assessment process. MCA can take various forms, and there are numerous potential methods and techniques. The outcome of an MCA can vary from a single 'score' for each option to a 'triple bottom line' score to a non-aggregated assessment against each criteria. Different approaches will suit different situations and decision-making contexts.

Where to look in the paper

Some sections of the paper that might be of particular interest to reader groups:

- Section 2.2.2 provides an introduction to CBA, CEA and MCA as the main decision-making frameworks available for incorporating sustainability impacts. It also explains why CEA and MCA are the approaches primarily addressed in this paper.
- Section 2.2.3 delineates the seven characteristics of 'good practice'.
- Section 2.3.1 covers the issue of stakeholder participation and the place of stakeholders within governance arrangements for sustainability assessment.
- Sections 2.4.1 and 2.4.2 provide details on the challenges of identifying, estimating and measuring externalities in order to make the links from the source of an externality through to who is affected.
- Section 2.4.3 discusses the difficulties raised for extended CEA by 'intangible' impacts that cannot be valued in dollar terms.
- Section 2.5.3 discusses how MCA can be used with the existing IRP framework.
- Section 2.5.4 explores the strengths and limitations of an MCA decision-making framework.

What are the take-home messages?

A sustainability assessment of urban water options should involve examining all the potential solutions on their merits for a particular location.

Regardless of the decision-making framework selected, how to muster the resources, capacity and willingness to strive for good practice should be the main considerations. Determining how to do either MCA or extended CEA well will be more important in the end than which approach is selected.

This paper sets out six common steps that should be discernible in any sustainability assessment of options for urban water. Together, the lists of six common steps and seven 'good practice' characteristics can be used as a checklist for practitioners designing their own assessments.

2.1 Introduction

The Australian IRP framework, as described in Turner et al. (2010), is designed to guide water utilities in planning for the provision of water services across long-term planning horizons. This type of strategic planning for urban water involves seeking a set of options which together will achieve a specified objective, across a set time period and within regulatory limits. The goal of the overall IRP process is to determine which options to recommend in a final strategic plan.

Traditionally, a key element of IRP is the comparison of options on the basis of least cost as measured by a CEA. While the cost of implementing a strategy will always be an important consideration in water planning, water utilities are increasingly looking to incorporate into their decision making a broader range of sustainability impacts that are not conventionally captured in a CEA.

Despite the widespread recognition of the importance of sustainability assessment, there is a lack of guidance for urban water planners on how to choose between different decision-making frameworks to incorporate sustainability. The WSAA sustainability framework, documented in Lundie et al. (2008a) and referenced throughout this paper, provides guidance on the use of MCA. However, there is limited tailored guidance available on the use of CEA or even CBA for sustainability assessments in urban water. This paper seeks to fill some of those gaps by describing and comparing the CEA and MCA frameworks, methods and tools that could enable the assessment of economic, environmental and social impacts within IRP for urban water. While the same techniques for economic evaluation of externalities can be used with either approach, the paper focuses on CEA rather than CBA because CEA aligns with the IRP framework.[1]

2.1.1 Outline of this paper

This paper has six main sections:

- Section 2.2 provides background and answers three questions: why is sustainability assessment important in IRP and urban water planning more generally, what are the possible decision-making frameworks, and what constitutes good practice?
- Section 2.3 addresses the broad question of which initial issues need to be considered when selecting an appropriate decision-making framework and sustainability assessment method for urban water planning in a region. This includes the overarching issues of how a sustainability assessment will sit within the governance arrangements for water planning in that region, and therefore what forms of stakeholder or public participation will be appropriate.
- Sections 2.4 and 2.5 describe the frameworks, methods and tools for CEA and MCA approaches, respectively. The sections provide details on how sustainability impacts can be identified, estimated and measured within each of the frameworks. The strengths and weaknesses of the two approaches and the implications of choosing between the methods and tools associated with them are discussed.
- Section 2.6 outlines the issues that need to be considered when the results of sustainability assessments are integrated back into an urban water planning process.
- Section 2.7 draws conclusions and sets out key next steps for prospective water planners.
- Section 2.8 provides a list of further resources on relevant topics and studies that provide examples from around Australia.

2.1.2 Scope of this paper

The purpose of this paper is to provide potential users of the Australian IRP framework and other water planners with enough background on how to incorporate considerations beyond direct cost into water planning so that they can make decisions about which methods best suit their situations. It should be of value to those interested in either ‘triple bottom line’ assessment, incorporating externalities, or sustainability assessment more generally. It aims to enable water planners to either develop a brief of works for an assessment (and for evaluating consultants’ proposals) or to develop a plan to do the works themselves.

This paper aims to inspire readers to incorporate an assessment of a broad range of sustainability impacts into their water planning practice. The paper does not provide a step-by-step guide on how to conduct a sustainability assessment within either a CEA or an MCA framework. Rather, it shows the reader how to use existing resources, such as the WSAA sustainability framework (Lundie et al. 2008a), together with the Australian IRP framework.

The primary intended audience for this paper is urban water planners working at the scale of a single utility’s area of operations or planning for a particular water system, although it will also interest others in the urban water and water planning fields. It has been assumed that readers are not completely new to this area and may have looked at the final plans of other utilities and discussed urban water planning processes with more experienced practitioners. It

[1] See the overview section in Turner et al. 2010 for a discussion of why the IRP framework utilises CEA in comparison to CBA.

is assumed that readers will have heard of MCA and CBA and possibly CEA, but that this paper may be the first they have read that explains the differences and compares the approaches in the context of sustainability assessment for urban water.

On the question of how the material presented in this paper relates to the existing IRP framework as set out in Turner et al. (2010), the paper's primary goal is to inform the sustainability assessment of options and portfolios of options. This is Step 3 of the existing IRP framework ('Develop the response'—see Figure 1.1). Details of the alternative approaches to sustainability assessment provided in the background section (Section 2.2) as well as in sections 2.4 and 2.5 are directly relevant to Step 3. Those sections describe how the sustainability impacts of options and portfolios might be assessed when taking either a CEA or MCA approach.

This paper also addresses Step 1 of the existing framework ('Plan the overall process'). The question of what needs to be considered when selecting an appropriate approach to sustainability assessment is covered in Section 2.3; indeed, the paper as a whole should inform the initial planning phase of an urban water planning process.

This resource paper and Turner et al. (2010), *Guide to demand management and integrated resource planning for urban water*, does not replace the need for water planners in specific regions to look first to the guidance provided by the relevant state government department. For example, in New South Wales the Department of Water and Energy has IWCM guidelines for water planning by non-metropolitan water utilities. Those guidelines require triple bottom line assessment of options. In Victoria, the Department of Sustainability and Environment has guidelines for water planning by non-metropolitan water utilities. Relevant state government guidelines are included in Section 2.8 at the end of this paper.

2.2 Background

2.2.1 Why is sustainability assessment important?

Since the Bruntland Commission was convened in 1983, sustainable development and sustainability have emerged internationally as one of the fundamental and overarching goals of public policy. The concept of sustainability implies that whatever is done should be done in a manner that will not harm future generations. It implies a more 'holistic' understanding of the relationships between the social, economic and ecological aspects of any problem or situation. It also implies that what we do should not destroy critical life-supporting capacities of ecological systems. By definition, 'sustainability assessment' should enable decisions about how resources are allocated and managed in order to achieve sustainable outcomes.

The concept of sustainability encompasses not only environmental and ecological systems, but also the social and economic dimensions of society, as well as the interactions between those dimensions. The triple bottom line categorisations of economic (or financial), environmental and social impacts are a useful guide to sustainability assessment, which may also be expanded to include technical risks and public health impacts. For example, Lundie et al. (2008a:6) observe that:

> To assist the urban water industry to achieve sustainable use of scarce water resources, the industry needs to develop a methodology for evaluating the sustainability of the various supply and demand options taking into account economic, environmental, human health, technical and social considerations.

Existing frameworks and guidelines have identified the importance of including sustainability impacts in urban water management and planning, including in IRP (Ashley et al. 2004, Mitchell et al. 2007, Lundie et al. 2008a, Turner et al. 2010). This includes impacts on biodiversity, recreation and amenity, greenhouse gas emissions, and river health. In the context of IRP for urban water, decisions about which options and portfolios of options to implement should be informed by an assessment of how the different choices would affect sustainability. However, despite existing guidelines, the assessment of the environmental, social and other 'non-market' aspects of sustainability in urban water management and planning remains limited (Turner et al. 2010).

Significantly, it is often the environmental and social aspects of decisions not reflected in market transactions that represent the most substantial value for individuals, communities and society. It can be argued that if stakeholders are to regard an urban water planning process as credible, and hence if the resulting decisions are to be politically acceptable, planners must explicitly take into account both direct costs and non-market considerations, as well as the trade-offs between them. This is because sustainability assessment attempts to include society's broader values in the selection of options for urban water.

An assessment of the sustainability impacts, whether as environmental, social and other criteria or as non-market impacts (externalities), is indicative of taking a 'whole of society' perspective to options analysis. Such a perspective is the appropriate one for water planning. However, tensions may exist between the results of an analysis from a whole-of-society perspective and the results of an analysis from a water utility's financial perspective. In the context of options analysis for IRP, the tensions are addressed through having a number of alternative 'cost perspectives', including a societal and utility cost perspective (see Step 3C in Turner et al. 2010). Alternative cost perspectives do not by themselves resolve the tensions, but they highlight issues such as the loss of revenue from water sales when potable water is conserved. How easily tensions are resolved will depend on the institutional arrangements governing water planning in a given region.

In short, sustainability assessment is necessary if decision makers are to make good decisions when planning urban water systems and be perceived as making good decisions. Good decisions do not cause significant unexpected adverse impacts, do not result in unnecessary harm, and are acceptable to the community. It is hoped that they are also decisions that will be looked back upon as having been the right ones.

2.2.2 What are the possible approaches to sustainability assessment?

This section introduces the main decision-making frameworks available for incorporating sustainability impacts into the assessment of urban water management options: CBA, CEA and MCA. Of the three, CBA and CEA are presented separately but share many common techniques for estimating the monetary values of non-market impacts.

Cost–benefit analysis involves estimating monetary values for all future benefits and costs of alternatives under consideration. The nature of the alternatives will depend on the context and the objectives of the CBA study. For example, it could focus on a change to urban water policy, a demand-management program or a single infrastructure development. A recommendation can then be made to implement one or more alternatives expected to have a net benefit to society—that is, those for which the total benefits outweigh the total costs.

By translating all impacts, sustainability or others, into monetary terms, CBA provides a methodological framework for systematically including all financial, social and environmental impacts into a decision in dollar terms (see Box 2.1). Various methods are available to assign a monetary value to sustainability impacts that are not traded in markets, and hence have no market price. Those impacts could include effects on values from biodiversity to amenity and recreation (see Section 2.4 for further discussion). CBA also involves a systematic 'discounting' of the streams of future benefits and costs to account for the time preference for money. This reflects the idea that consumption now is worth more than consumption in the future. Valuation is therefore sensitive to the choice of discount rate, and this aspect can be a concern for some stakeholders when applied to particular sustainability impacts (see Box 2.5 in Section 2.4).

Box 2.1: Assumptions and principles underlying cost–benefit analysis

The foundations of CBA lie in welfare economics; it therefore incorporates the key assumptions that:

- the level of welfare for the whole of society is the sum of the welfare of each individual
- the option that offers the highest net benefit should be the preferred option for society
- the level of welfare for the whole of society can be measured in dollar terms.

In other words, CBA assumes that, while there may be winners and losers from a particular alternative (some individuals and organisations will benefit, whereas others will bear costs), government can redistribute the gains from winners to losers, leaving everyone better off. It further assumes that impacts of all types can be represented as dollar costs or benefits.

Some critics of CBA believe that these key assumptions abstract too far from reality and that, therefore, decisions made solely on the basis of a CBA study may not ultimately maximise social welfare.

Proponents of CBA agree that it should not be the sole decision-making criterion in any given situation. They also point to methodological developments that can improve CBA, if not completely resolve the theoretical issues raised by critics.

Sources: Gowdy (2003), Spash et al. (2005), OECD (2006).

CBA is generally the preferred decision framework recommended in Australian and state government guidelines for regulation, project and policy appraisal (see, for example Queensland Treasury 2002, Commonwealth of Australia 2006, Government of Victoria 2007). It is also the methodology recommended in the Council of Australian Governments' best practice regulation guide (COAG 2007). However, for the reasons given below, this paper focuses on the simpler CEA methodology. CEA is also an accepted economic appraisal method (NSW Treasury 2007, Queensland Treasury 2002, Government of Victoria 2007).

While CBA can be used to compare demand and supply options, placing a value on the water supplied or saved in the context of a supply–demand plan is not nessarily as simple as applying the current per kilolitre price of water. Equally, a previously calculated long-run marginal cost of supply cannot nessarily be used. This is because both the water price and the marginal cost will vary depending on the outcome of a supply–demand plan (see the overview section in Turner et al. (2010) for a discussion of using CBA in comparison to CEA in urban water supply–demand planning. Given these issues, the main role for CBA in urban water planning is more likely to be at the point of environmental impact assessment (EIA) of large-scale individual projects, such as new dams, desalination plants or water recycling plants.

Cost-effectiveness analysis, like CBA, involves valuing benefits and costs of options in monetary terms—the difference is that the main benefits of alternatives are measured in physical rather than monetary terms. The decision metric is then the net dollar cost (or the dollar cost per unit) of achieving the underlying objective.

CEA is a useful technique when it is easier to identify benefits and measure them in physical terms, rather than assign a dollar value (Mitchell et al. 2007, Government of Victoria 2007). It is best applied where the various options being considered will result in the same or comparable outcomes. It is therefore well suited to urban water planning situations, such as supply–demand planning, where the levels of service are commonly predefined by regulated standards. Ideally, the levels of service standards will also reflect community preferences (Erlanger and Neal 2005). In this way, CEA allows options to be ranked and compared on the basis of least (net) cost to meet a previously agreed objective.

In the current IRP framework, CEA is used to estimate the (net) cost per kilolitre of water saved or supplied by each individual option. From this ranking of the options, portfolios of options that all meet the same objective (for example, providing a secure water supply over the study period) are then developed and compared according to their relative (net) cost in another CEA. The IRP framework guidelines (Turner et al. 2010) suggest that some sustainability impacts can be incorporated into IRP via monetisation and inclusion in an extended CEA. However, beyond greenhouse gas emissions, the monetisation of sustainability impacts has not occurred in most IRP studies to date.

Proponents of CBA argue that cost-effectiveness can only be a partial evaluation of options because not all benefits are valued in dollar terms. Consequently, they argue that CEA cannot help with the decision about whether or not the underlying objective is itself worth public investment (OECD 2006). This is true, but in practice CEA is used extensively to evaluate public investments in the health, safety and education sectors, where the case for pursuing particular public policy goals has already been established through other political, institutional or consultative processes.

Security of urban water supply could arguably be one such type of public policy goal. This is not to say that community input into the parameters of a 'secure water supply' is not required, but rather that processes other than CBA may offer more pragmatic, defensible and representative ways to capture society's preferences in the formulation of overriding public policy goals. Due to CEA's alignment with the existing IRP framework, this paper focuses on CEA rather than on CBA. Nevertheless, the guidance material on economic evaluation is equally relevant to CBA.

Multi-criteria analysis is an alternative framework for decision making, and involves using multiple criteria to assess options. Unlike CEA and CBA, MCA does not require the monetisation of all impacts, although there may be some criteria for which indicators can be measured in dollar terms. MCA requires a mechanism for selecting the criteria on which alternatives will be measured or ranked, as well as a mechanism for making trade-offs between criteria. At its simplest, trade-offs can be made by weighting criteria against each other.

MCA frameworks have been applied in urban water planning in numerous locations, are encouraged by government department guidelines such as the IWCM guidelines in New South Wales, and have been documented by a decade of literature. Examples of urban water planning applications of MCA include the Eurobodalla IWCM study (DPWS 2003), the Gold Coast Waterfutures project (Lundie et al. 2008b) and WA Water Corporation's Water Forever project (Water Corporation 2008c). Literature supporting the application of MCA to water planning includes academic papers describing various approaches and criteria sets, as well as a number of water industry guidance documents on the practical application of MCA to urban water planning (for example, Lundie et al. 2008a and Ashley et al. 2004).

MCA explicitly recognises that decision making may involve multiple objectives and multiple viewpoints, and that in complex situations trade-offs will need to occur between objectives. It acknowledges that complex decisions are rarely made by one person or on the basis of a single metric, such as dollar cost alone (Lundie et al. 2008a). While MCA can be used in sustainability assessment, it can also be embedded in a larger set of techniques or steps that are applied to assist in structuring decision making or developing a coherent preference selection among stakeholders in complex situations.

The principal objective of many MCA frameworks is to support the decision-making process in identifying the option most preferred by the selected stakeholders (Roy 1991). This process captures sustainability impacts that are identified as important by those stakeholders. The selection and use of agreed decision criteria are central to this process. Approaches to MCA vary, based on how stakeholders are selected, how they express their preferences and how those preferences are captured in mathematical terms to enable a comparative assessment (Lundie et al. 2008a).

The OECD (2006) observes that MCA tends to be more 'transparent' than CBA because all the objectives and criteria are usually clearly stated, while the assumptions underlying the objectives of a CBA are not usually made explicit. However, critics of MCA argue that in practice it is not as 'accountable' as CBA, because scores and weights are often chosen by a small group of experts rather than a wider representative group covering all stakeholders (OECD 2006). Nevertheless, these are issues of application rather than fundamental characteristics of the various decision-making frameworks, and CBA, CEA or MCA can be conducted in ways that are both transparent and participatory.

It is important to remember that, whatever framework is used, bringing sustainability impacts into decision making for urban water necessarily involves processes of simplification and codification. As a result, some sustainability impacts and types of values may be given greater recognition than others in the overall decision-making process. For this reason, decisions about which approach and methods to use for sustainability assessment need to be carefully considered and transparently communicated.

2.2.3 What constitutes good practice in sustainability assessment?

Despite variations between decision-making frameworks, there are a number of common characteristics that can be used to judge good practice in the assessment of sustainability impacts for urban water planning.

Good practice is characterised by:

1. An approach aligned with the governance situation in the region
2. A structured assessment framework
3. A method appropriate to the circumstance and scale of the decisions
4. The application of a systems understanding when identifying impacts
5. The use of robust estimates of the magnitude of impacts
6. Clarity in the treatment of uncertainty
7. Transparent valuation and reporting.

Aligned with the governance situation

A sustainability assessment should be aligned with the existing governance situation in a given region. This includes ensuring consistency with current state government policy covering water planning and recognising the existing institutional arrangements. It also involves considering the range of stakeholders in water planning decisions and their potential desire for participation or representation in any assessment of options.

Structured assessment framework

Various authors stress the importance of a structured framework to guide the process when incorporating sustainability impacts into an assessment (Lundie et al. 2008a, Bowers and Young 2000). This is because, to make an informed choice, all options must be considered in a consistent manner across the same period of analysis, the same spatial scale, using the same criteria, and the same decision metrics. A structured assessment framework provides the basis for justifying a recommendation for a particular option or portfolio.

Another of the reasons cited for a structured framework is to provide ‘markers’ to return to when inevitable iterations occur. The acceptance of the possible need for iteration is a common theme in guidance on options assessment for urban water (Lundie et al. 2008a, Turner et al. 2010).

Appropriate method

The approach selected needs to be appropriate to the scale of the decisions that are being informed by the assessment, as well as the circumstances of the water utility or water planning organisation. Those circumstances include the prevailing institutional arrangements and the available resources, including the skills and capacities of staff.

These first three characteristics of good practice are the basis for Section 2.3 of this paper.

Identifying impacts through a systems understanding

A sustainability assessment first requires the identification of the potential impacts that will be considered in the study. In relation to sustainability assessment of urban water options, this paper argues that the best approach to comprehensively identify the potential impacts is through developing a 'systems understanding' of the urban water options. Alternatively, a previously developed list of impacts or criteria that is based on such a systems approach can be consulted.

Importantly, developing a systems understanding will involve the explicit definition of the urban water system, with the options, the system boundaries and the surrounding systems included. A systems approach provides both a method for the analyst to systematically identify impacts and a means to demonstrate that important impacts have not been excluded. It shows clearly the extent to which secondary or flow-on effects are to be considered inside the assessment. Without this, the basis on which some impacts are included and others are not may be, or may seem to be, arbitrary. Also, defining the system and its surrounds should make it easier to determine what the links are in the chain of cause and effect from the system to the impact that will be assessed.

Robust estimates of the magnitude of impacts

Before placing a value on a sustainability impact, it is necessary to determine the magnitude of that impact. From a systems perspective, this can be viewed as a particular option altering the attributes of the urban water system, which in turn causes changes to flow to surrounding systems. Those, in turn, cause sustainability impacts.

Making a robust estimate of an impact requires a firm understanding of the cause and attribute links from the urban water option to the sustainability impact that is being valued. For example, a supply option that increases pumping from a river may increase turbidity, which would affect macro-invertebrates. This would affect native fish and therefore anglers. Estimating the impact on anglers relies on having an evidence base on which to estimate each of these magnitudes.

Most if not all impacts included in sustainability assessments will result from an initial physical cause. To estimate the magnitude of sustainability impacts one must first determine the magnitude of the initial physical cause before determining the magnitude of each of the causal links. This usually requires direct measurement, estimates based on modelling of the available biophysical data, or both.

Sections 2.4 and 2.5 address in detail the methods for identifying sustainability impacts and estimating the magnitude of impacts in relation to MCA and CEA, respectively.

Clarity in the treatment of uncertainty

There will always be uncertainties in assessments of sustainability impacts. Commonly, the uncertainties will be significant and may also arise at each link in the chain from the option to the impact. Some uncertainties are quantifiable. For these, risk assessment methods exist. However, it is likely that significant uncertainty will remain with some physical measurements and/or valuations of some impacts.

Good practice involves separating those uncertainties that can be dealt with via risk assessment from other forms of uncertainty where the unknowns are greater. Risk can be addressed analytically because both the magnitude and the probability of impacts are known or can be estimated. Where real uncertainty exists, probabilities or magnitudes are unknown. Parameters can sometimes be dealt with via sensitivity analysis, but uncertainties may also need to be simply acknowledged.

Transparent valuation and reporting

Transparency in reporting—and particularly in how values are assigned to impacts—is a key element of good practice and is important for the credibility of a sustainability assessment.

A transparent valuation method will inform decision making by illustrating how environmental, social and economic impacts are weighed up. This includes demonstrating how any trade-offs between particular sustainability impacts, and between sustainability impacts and direct costs, occurred. Transparency could also mean acknowledging whose values are being included in the assessment and how (for example, consumer values in a CEA via a survey, or stakeholders in an MCA meeting).

More generally, transparent reporting is important for ensuring the credibility and defensibility of the overall decision process. As a key medium for communicating with stakeholders, communities and constituents, reporting facilitates accountability. That is, reporting allows organisations that are making decisions about investment of public money for urban water outcomes to demonstrate, and be held to account for, the reasoning behind their decisions.

These last two characteristics of good practice are expanded in Section 2.6.

2.3 Planning the overall assessment process

This section addresses issues that need to be considered when designing a sustainability assessment process for urban water planning in a region. It outlines how to select an approach that is aligned to the governance context, while accounting for the potential for iteration as well as the internal circumstances of the water utility.

2.3.1 Accounting for governance and participation

The starting points for a consideration of governance will be the current state government policies covering urban water planning for the particular region; the local, state and national regulatory arrangements dictating levels of services, environmental licensing and planning consent; and, where applicable, the state government urban water planning guidelines (see Section 2.8). Together, these form the existing institutional arrangements with which sustainability assessment as part of an IRP process would need to align.

However, governance is not only about compliance with current regulations. Urban water planning decisions are often complex and involve multiple interests, and the finer points of a decision-making process in any given situation will defy capture within generic guidelines. A consideration of governance requires a consideration of the wider stakeholders in water planning decisions and their potential desire for participation or representation in the assessment of options.

Stakeholder participation is a key principle of IRP (Turner et al. 2010), and identifying stakeholders is a part of Step 1 of the IRP framework. However, there is limited guidance in Turner et al. (2010) on who to involve and how to involve them. Questions about who participates are particularly important for sustainability assessment because, as stated in Section 2.2.1, sustainability assessment is an attempt at representing society's broader values in the selection of options for urban water.

Identifying stakeholders

Identifying who to involve in water planning begins with the definition of 'stakeholder'. A United Kingdom guide, *Sustainable water services: a procedural guide* (Ashley et al. 2004:79), defines stakeholders as 'Any individual or group which has a stake in how water and wastewater services are delivered, and could include customers, employees, environmental and community groups'. Many water utilities will already have a similar definition in use. Lundie et al. (2008a:17) develop this further by outlining, as a starting point, a checklist of possible stakeholders for Australian water utilities:

> [the] water authority, owner developer, consent authority, local government, state or federal government departments, residents, community groups, environmental groups, small business/industry groups, consumer groups, indigenous groups, catchment management groups and farmers.

There are three types of stakeholders represented in this list:

1. The first type, institutional stakeholders, have direct power over whether a particular urban water option can be implemented. They include the water utility's executive, the planning and environmental consent authorities, the pricing regulator, local government, and various state and federal government departments. They also include an owner or developer of a site who has rights under property law. These stakeholders are representatives of the existing institutional arrangements.
2. The second type of stakeholder represents the public, organised into groups. They do not have direct power but may wield influence because they are organised into representative groups for political engagement. These include groups representing local business interests, specific industry groups (such as land developers), trade unions or trade councils, pensioner groups and environmental groups.
3. The last type of stakeholder is the general public, acting individually. They include the average residential water user and are not politically organised or necessarily represented by a specific group.

These three types of stakeholders are quite different, and their participation in a given sustainability assessment or water planning process will require different mechanisms.

For the institutional stakeholders, obviously any water planning process will endeavour to meet the prescribed requirements of that group. However, beyond that, the appropriate extent of stakeholder participation, including public participation, becomes less clear-cut.

Public participation

Many authors have argued for a role for public participation or community engagement in decision making about public infrastructure, such as urban water systems. The United Nations Brisbane Declaration on Community Engagement (2005) states that community engagement:

- is critical to effective, transparent and accountable governance in the public, community and private sectors
- generates better decisions, delivering sustainable economic, environmental, social and cultural benefits
- enables the free and full development of human potential, fosters relationships based on mutual understanding, trust and respect, facilitates the sharing of responsibilities, and creates more inclusive and sustainable communities.

There is, however, a potential tension in public participation between the participation of representative groups and the participation of individuals, such as residents, who are not affiliated with a group. Lundie et al. (2008a) acknowledge this tension, cautioning that some types of stakeholders may need more attention because they are not represented by established organisations or cohesive groups. Sussking (cited in Carson 2008) also sees this tension in the public participation field and notes that, while representatives of organised groups can feed information back to their respective groups and represent many voices, individuals speak only for themselves and therefore display a sample of the public's reaction rather than a representation of it. This distinction between individuals and group representatives needs to be addressed in the process used for stakeholder involvement; different engagement mechanisms may be required for the different types of stakeholders.

The International Association for Public Participation (IAP2) Australasia's Public Participation Spectrum outlines five levels of public participation with increasing public impact, from 'inform' to 'empower' (see Table 2.2).

Table 2.2: IAP2 public participation spectrum

Level	*Goal*
Inform[a]	To provide the public with balanced and objective information to assist them in understanding the problems, alternatives, opportunities and/or solutions.
Consult	To obtain public feedback on analysis, alternatives and/or decisions.
Involve	To work directly with the public throughout the process to ensure that public concerns and aspirations are consistently understood and considered.
Collaborate	To partner with the public in each aspect of the decision, including the development of alternatives and the identification of the preferred solution.
Empower	To place final decision-making in the hands of the public.

a Many practitioners stress that 'inform' is a passive process and could be better considered as a prelude to participation rather than as a form of participation (Carson 2008).
Source: IAP2 (2007).

The IAP2 spectrum is a useful reference for water utilities seeking to be transparent about the level of participation they are committing to, because each level is accompanied by an associated 'promise to the public' (IAP2 2007). For example, a commitment to consult may involve engagement mechanisms such as focus groups, surveys, public meetings and promises to the public that 'we will keep you informed, listen to and acknowledge concerns and provide feedback on how the public input influenced the decision' (IAP2 2007).

In comparison, a commitment to collaborate may involve mechanisms such as citizen advisory committees, consensus building and participatory decision-making (IAP2 2007). Such an approach promises the public that 'we will look to you for direct advice and innovation in formulating solutions and incorporate your advice and recommendations into the decisions to the maximum extent possible' (IAP2 2007). Specific techniques such as surveys, focus groups, citizen advisory committees and citizen juries require expertise and are likely to require the engagement of social researchers.

Ideally the public should also be involved in deciding what level of involvement is appropriate for them. For example, when the WA Water Corporation surveyed community members in the early stages of Water Forever planning (Water Corporation 2008a), it found that there was a range of preferred engagement levels within the WA community. Fifty-five per cent of respondents wanted the Water Corporation to 'consult'. However, a significant proportion (22%) of respondents indicated that they wanted less involvement, keeping to the 'inform' level, and about the same proportion (23%) preferred the higher level 'involve' style of engagement.[2] These preferences were incorporated into the Water Corporation's next stages of planning (Water Corporation 2008b).

Section 2.8 includes further resources specifically on the issue of public participation.

Implications for selecting the decision-making framework

The level of stakeholder participation decided on may influence the methodology that is then selected for options assessment. For example, it is technically possible to include stakeholder values in an extended CEA in a methodologically robust way without, or with only limited, stakeholder participation. This is not the case with MCA. Likewise, while there is significant potential for an 'involve' level of participation in a CBA, a 'collaborate' level of participation may prove more difficult because the CBA frame of analysis (the criteria or the decision metric) is already set.

Despite this, in either CBA or CEA stakeholder participation is a highly effective means of identifying and mapping all the stakeholder groups, as well as mapping out which non-market impacts exist and who would be affected. Estimating stakeholder impacts can also involve significant engagement with stakeholders. Methodologically, stakeholder participation in an extended CEA through interviews or workshops provides a clear and defensible technique for identifying impacts, identifying affected stakeholders, and estimating those impacts on stakeholders in dollar terms. There is also potential for 'collaborate' level participation in an

[2] Note that the range in the question was limited to whether respondents preferred an 'inform', 'consult' or 'involve' approach.

extended CEA, in which stakeholders are involved in defining the objectives that cost-effectiveness will be assessed against.

For advocates of MCA, a particular strength of the approach is the potential for stakeholder participation in both the selection and the valuation of criteria. The WSAA sustainability framework process is based on the use of stakeholder steering committees—a process of ‘collaboration’ that may be accompanied by other public participation opportunities at lower levels. One example of such ‘collaboration’ is the Gold Coast Waterfutures project. MCA has also been used for other levels of public participation. For example in its Water Forever process, the WA Water Corporation applied MCA for options analysis using a process informed by the WSAA framework but the commitment was to ‘involve’ the public rather than to ‘collaborate’. The Water Corporation published its *Reflections: community engagement report* (Water Corporation 2008b) to show how community input had been gathered and how public concerns and aspirations had shaped the criteria and options used in its internal MCA process.

With any form of stakeholder participation beyond the level of ‘inform’ will come the potential for stakeholder ‘gaming’. Gaming refers to the idea that stakeholders will anticipate how their responses are going to be included in any final assessment and respond accordingly. Unless the assessment methodologies used are specifically designed to manage gaming, then an influence of stakeholder gaming on the assessment should be expected. It is only natural that stakeholders will have an interest in particular outcomes.

For critics of MCA, the potential for stakeholders to influence the selection of assessment criteria is a particular issue. However, there are also risks of undue influence from stakeholder lobbying or gaming of specific methods in monetary valuation.

Monetisation methods such as ‘choice modelling’, because of the more sophisticated framing of alternatives, can counter the influence of survey respondents gaming their responses. Choice modelling asks respondents to choose between more than two alternatives, each of which is described by multiple attributes. This forces respondents to ‘trade off’ between attributes and enables implicit values for the attributes to be estimated (Morrison et al. 2002).

In MCA with a stakeholder steering committee, the reality of gaming may simply need to be acknowledged and managed through the selection of a wide range of stakeholders with representative views. It will also be important to maintain some control over the selection criteria so that the final set is coherent and avoids criteria that overlap.

In summary, it is important to consider who the stakeholders are, the different ways they might be engaged in the assessment of options, whether there is a need to manage the potential for stakeholders gaming the assessment, and how stakeholder participation might also need to play a role in the wider IRP process.

2.3.2 Allow for a structured but iterative assessment

Urban water IRP is described by Turner et al. (2010) as ‘a complex task involving multiple (and often conflicting) objectives, stakeholders, options, risks and uncertainties’. They cite this complexity as necessitating a structured, iterative approach. The need for a sustainability assessment framework to provide structure and an acceptance of iteration are themes common to the assessment of options for urban water from both multi-criteria and economic perspectives (Lundie et al. 2008a, Bowers and Young 2000). These themes are not limited to urban water planning; rather, they emerge in literature about public policy and decision making in all its forms (Deleon 1999). Two of the reasons given are that they enable planners to work systematically and ‘know where they sit’ based on ‘markers’ in an established structure, and that a coherent framework supports a transparent justification for the recommendation of options.

An iterative approach is necessary because it acknowledges that the real world of strategy formation is rarely as straightforward as a linearly structured process implies. Referring to the practice of policy development generally, Deleon (1999:28) notes that:

> Policy analysis is invariably iterative because in practice things are seldom tidy. Information is often incomplete, people disagree over objectives, parameters shift, policy

analysts must be reconciled to developing options and testing them … and then working them through again and again.

This type of policy untidiness will be familiar to water planners.

The role of iteration in a sustainability assessment is also addressed by the United Kingdom Department of Communities and Local Government (DCLG), which states that the underlying aim of an assessment should be to 'reflect the informed preferences of people as a whole' and that this requires the iteration of the analysis[3] until a 'requisite model has been obtained' (DCLG 2009:70). A 'requisite' model is described, following Phillips (1984, cited in DCLG 2009:70), as one that is 'just good enough to resolve the issues at hand'. This advice dictates that the assessment should only be the minimum necessary to reach a resolution of the key issues. The DCLG argues that, while people often find it difficult to rely on approximate or 'rough-and-ready' inputs, an initial up-front analysis combined with sensitivity analysis will help to show what data really matters in selecting between options.

The potential need for iterations in an assessment only reinforces the need for a structured framework, because it is only with a structured and coherent framework that both the water planner and all participants are able to identify 'where we are at' in both the options assessment process and the wider decision-making process. Lundie et al. (2008a) note that an explicit structure supports the participation of stakeholders by providing a reference point should iterations occur.

For practitioners following the current IRP framework, as outlined in Turner et al. (2010), a level of structure comes from conducting a sustainability assessment within that framework.

2.3.3 Matching the assessment to the circumstances

A key 'good practice' characteristic raised by practitioners is 'matching the assessment to the circumstances'. In other words, ensure that the assessment will be adequately resourced. This also covers the need to select a method that is appropriate to the scale of the decisions it aims to inform and reflects the situation of the water utility or water planning organisation.

Whatever approach to sustainability assessment or options assessment is chosen, there will be important common considerations. In addition to the consideration of the current institutional arrangements and potential need for stakeholder participation (as discussed in Section 2.3.2), it is necessary to ensure that the assessment is systematic, rigorous and transparent. To ensure those qualities, adequate resources must be provided. Adequate resourcing means the provision of adequate time, funding and skilled people. Consideration must be given to the resources needed to conduct the technical analysis, to use the assessment method selected and to coordinate the participation of stakeholders.

The type of sustainability impacts, organisational expertise and technical data available to an organisation should also influence the selection of the assessment method. For example, MCA approaches generally require biophysical data linked to each of the criteria for each of the options, whereas to implement CEA both biophysical data and relevant monetary valuations are required.

Different considerations inform the resourcing of the stakeholder engagement, which also links to the assessment method selected. To be done well, MCA, for example, requires stakeholder engagement. The resources needed for stakeholder engagement with MCA include time to initiate and manage these interactions, facilitation skills, the resources to allow stakeholders to be involved in workshops, and the in-house capacity to run such engagement processes.

One tool for considering the implications of alternative approaches is to think through prospective approaches using a set of steps that are common to all. These are:

1. Drawing boundaries and establishing baselines

2. Recognising the requirement for further assessment of impacts of options not represented in the analysis of direct costs

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[3] The DCLG is discussing an MCA , but the principle can be extended more broadly.

3. Identifying the impacts to include in a broader assessment
4. Estimating the magnitude of each impact
5. Placing a value on each impact
6. Interpreting and communicating the results.

The resourcing implications of each step can then be taken into account. In conducting a comparison of alternative approaches, there is much in common in the resources required to apply the two approaches. For example, a well-conducted extended CEA may use stakeholder consultation to identify the sustainability impacts and stakeholders affected and then conduct an options assessment internally. It is also possible to use focus groups as a means to engage the public on questions about which sustainability impacts can be monetised and which cannot, and what are acceptable valuations to include in an assessment. This process would have similar resource requirements to the MCA process described by Lundie et al. (2008a).

Having the resources to do well whichever method is selected should be the most important consideration. There is likely to be a greater difference between a poorly done CEA and a well-done CEA than between a well-done MCA and a well-done CEA. Given this, the key consideration when selecting an approach should be 'what will we be able to adequately resource and therefore do well?'

2.4 Options and portfolio analysis using extended CEA

The key characteristic of the CEA framework is that it is used for comparing alternative options for meeting the *same objective* (Hanley and Spash 1993). As discussed in Section 2.2.2, CEA differs from CBA in that the value of the underlying objective—such as the provision of secure urban water services—is not itself measured, but is taken as a necessary goal for society. The decision-making metric in CEA is the net dollar cost (or the dollar cost per unit) of achieving the underlying objective. In this way, the least-cost set of options to meet the required goal can be selected. In IRP for urban water supply–demand planning, both the unit cost of water saved or supplied for individual options and the net present value (NPV) of portfolios are assessed based on relative cost-effectiveness.

Incorporating values for sustainability into this framework involves measuring how various options and portfolios of options affect sustainability, and valuing those impacts in monetary terms. As discussed in Section 2.2.2, an inherent challenge is that, unlike many of the direct costs and benefits of urban water options (such as the costs of construction, or avoided energy costs of water efficiency programs), many of the impacts on environmental or social sustainability are not reflected in market transactions or are only reflected indirectly. For example, an urban water option could result in changes to downstream habitat and biodiversity, which in turn could affect recreational, amenity, tourism and commercial fishing values. For biodiversity, recreational and amenity values, there is no immediate 'price' that can easily be used to value the impacts, so valuation studies would be needed. In the case of tourism and commercial fishing values, while market prices do exist, the likely extent of any impacts that would be caused by the option in question needs to be demonstrated. Together, these two types of non-market impacts are referred to as 'externalities' (see Box 2.2).

This section outlines ways of identifying sustainability impacts, focusing on the economic valuation of non-market sustainability impacts (externalities). It then addresses the question of how those externalities can be measured and valued in dollar terms. There is a focus on environmental externalities or changes to values that arise out of impacts on the biophysical environment, but some of the key considerations are also given to social sustainability impacts. A final subsection outlines the strengths and limitations of economic valuation methodologies and an extended CEA approach to sustainability assessment.

Box 2.2: What is an externality?

Definitions vary, but broadly externalities are the unintended side effects (or 'spillover effects') of an action taken by one party that affect the welfare of another party and have not taken place through a market transaction between the parties. Externalities may be positive or negative.

The definition of externality is useful to consider when identifying sustainability impacts for incorporation into an option assessment, because it requires specifications from cause through to effect. That is, it requires identification of the entity undertaking the activity that causes a change in the biophysical environment, which in turn has an impact on a third party or stakeholder, whether that be an individual, an organisation or the wider community.

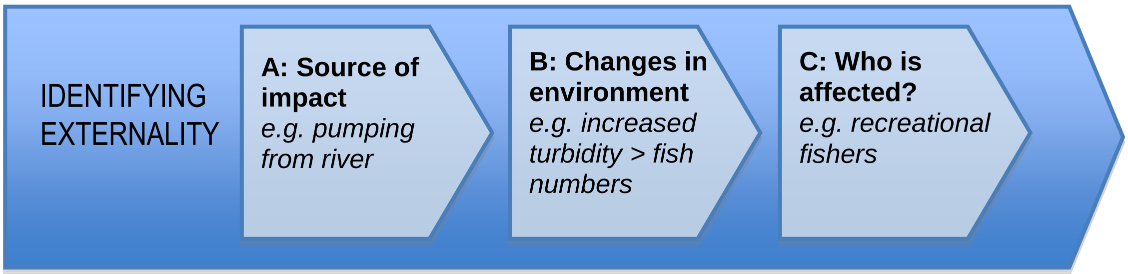
Bowers and Young (2000) provide a useful framework for considering externalities from urban water and describe a process of measuring externalities as identifying some sort of 'dose–response' model. They specify that 'dose-response modelling has to extend from the actions of the individual or body that is causing the externality, to the response of the individuals or bodies who perceive the external effect' (Bowers and Young 2000:33). This means that in identifying sustainability impacts for CEA, it is essential to identify who will be affected, because that will in part determine the magnitude of the cost or benefit.

2.4.1 Identifying sustainability impacts

As discussed in Section 2.2.3, adopting a systems understanding when identifying and measuring sustainability impacts of urban water options is a characteristic of good practice for a comprehensive assessment. This involves clearly defining the urban water system, the system boundary and those aspects of the surrounding systems that could be affected. It involves drawing the boundaries of the analysis in terms of space, timeline and stakeholders (see Box 2.3 at the end of this section, on applying a systems understanding to urban water systems).

For an economic valuation, whether under extended CEA or CBA, identifying the sustainability impacts of an urban water option will involve mapping how that option's attributes might cause changes to environmental or biophysical conditions, and then how those changes would affect various stakeholder groups. An example process for identifying impacts that are externalities is shown in Figure 2.1 and described in the following subsections.

Figure 2.1: A process for identifying externalities



Source: Adapted from Dwyer et al. (2006).

As in any options analysis, a baseline or 'base case scenario' will also be necessary for the period of analysis (Mitchell et al. 2007). This allows the impacts of all options to be compared against the same 'do nothing' scenario. The base case should include expected environmental, social, economic and policy changes over the analysis period.

A: Identify the sources of impact

Describing a sustainability impact of an urban water option involves first the systematic identification of those elements of the option that could have an impact on environmental or biophysical conditions—the 'source' of externality. The way those activities are described will depend on the planning objective and the types of urban water options being considered.

For example:

- Bowers and Young (2000), in their framework for valuing externalities across an entire system supply, categorise activities broadly under the economic services of water use, wastewater return, stormwater management and disposal.
- The Productivity Commission (2006), in its framework for valuing externalities caused by irrigation water use, categorises sources as those activities undertaken by suppliers of water (constructing, maintaining and operating supply infrastructure) and users of water (applying water to crops and pasture).

In identifying and describing potential sources of sustainability impacts, it is important to take a wider systems view. For example, a supply option will have potential sustainability impacts not only through its direct construction and operation, but also through its implications for the quantity or probability of how other components of the urban water system are then operated (for example, the amount of pumping for distribution or the likelihood of intercatchment transfers). This also applies to water-use efficiency options.

The systematic identification of sustainability impacts from urban water infrastructure systems should also consider impacts across the 'life cycle'. This might involve explicit and transparent descriptions of what potential sources of impact are included (for example, only the operational and use phases of the options) and what sources are not included (such as the production of materials that go into a system's manufacture).

As well as clarity about the system boundaries, being clear about what is in the baseline (for example, what activities would be undertaken in the business-as-usual case if none of the options is initiated) will aid in identifying which sources of sustainability impact should be attributed to the options.

B: Identify changes in environmental conditions

Once possible sources of externalities have been identified, the potential changes to the biophysical environment can be estimated. The changes might include alterations to hydrology, water quality, ecosystem health or air quality of the surrounding environment. They also include impacts such as expected increases or decreases in GHG emissions. Identifying potential changes in environmental conditions is required to enable the measurement or estimation of those changes in physical or biophysical terms; some level of modelling is commonly a part of such estimations (see Section 2.4.2 for further discussion of the measurement of physical impacts).

Again, clearly specifying the baselines for comparison is critical to the identification of changes in environmental or biophysical conditions attributable to the urban water option. For assessing future options, the relevant baseline will be the projected business-as-usual conditions rather than conditions at a point in time in the past (for example, the pre-European river regime).

Key variables in determining baselines are the current and expected policy and regulatory environments. Goals and limits, if they are set by regulation, are part of the boundary conditions for designing the options. For example, if water quality standards are expected to change in the near future, the new standards should be included in the baseline. This means that an assessment of options to improve discharge water quality to the new standard should not include the value of those improvements as a positive externality.

C: Identify who is affected by the sustainability impact, and how

Identifying the stakeholders affected by sustainability impacts is required in order to value those impacts in dollar terms. Affected stakeholders might be individuals or organisations; businesses, sectors or industries; or the local, regional, national or global community. There may also be overlaps between stakeholder groups.

Once again, a systems approach can be used to clearly map which stakeholders are considered in the assessment in relation to which impact. For example, a biodiversity impact might affect, among other things, recreational fishing catches. This fishing aspect of the biodiversity impact could be seen to flow through to suppliers of fishing equipment. When making the assessment, it should be clear whether the biodiversity impacts extend to include these flow-on effects or whether they are captured in a separate 'recreational fishing' impact. Also, as discussed in Section 2.3.1, while it is possible to assess externalities in a methodologically sound manner without stakeholder involvement, participation is an effective means of clearly and defensibly identifying which stakeholders are affected by which impacts.

Bowers and Young (2000) use the concept of having both 'tangible' and 'intangible' impacts in their framework of urban water externalities. Intangible impacts are real but not amenable to economic valuation methods. For Bowers and Young, impacts such as potential loss of human life, potential increased human suffering, and aspects of lost biodiversity and wildlife are considered 'intangible'. The idea of having intangible impacts is linked to stakeholder identification because, while some impacts are intangible on moral grounds, others are intangible because the specific stakeholders affected are hard to identify and those affected are diffuse.

The total economic value (TEV) framework is an alternative that is widely used for identifying the benefits of ecosystems, and how ecosystem values might be affected by policies and projects. It typically divides values into use and non-use values. TEV could be used for identifying how changes in environmental conditions resulting from urban water options have an impact on stakeholder values. This framework includes categories of values that extend beyond direct costs to include indirect values and values considered intangible. For example, Emerton and Bos (2004) describe how the TEV framework can be used to identify impacts to the ecosystem services associated with water catchments:

- use values—direct use values (for example, timber, fuel and food products); indirect use values (such as flood control, carbon sequestration and climate regulation); option values (for future possible uses)
- non-use values—existence values (intrinsic values irrespective of use, such as cultural, heritage and aesthetic values).

In all cases, once externalities have been identified, including the source the biophysical change and the stakeholders affected, a process is then needed for measuring and valuing those sustainability impacts.

Box 2.3: Applying a 'systems understanding' to urban water systems

A systems understanding aims to synthesise all the relevant information that we have about a phenomenon or object so we have a sense of it as a whole. It also involves understanding that the system exists within other larger systems (Kay and Foster 1999).

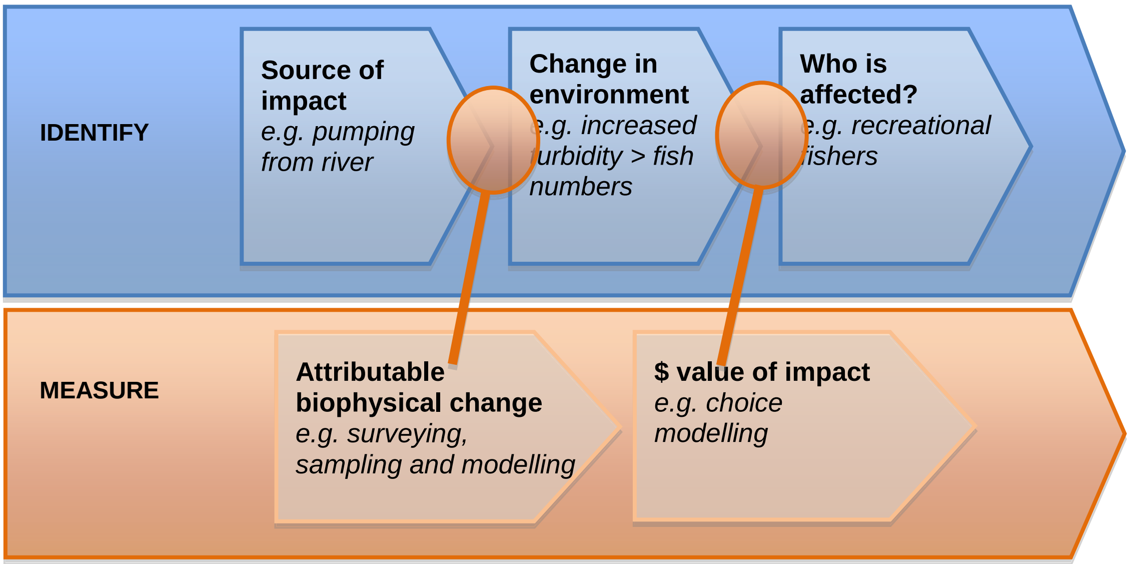
Applying a systems understanding to identifying sustainability impacts aligns with common understandings of sustainability. This is because of its environmental, social and economic dimensions, and the challenge of sustainability frequently being perceived as a systems problem. It also has the practical advantage of providing a means of systematically identifying impacts by considering the interaction of technical, environmental, social and economic systems. The temporal aspects or the life-cycle impacts on the system or the system components are an essential part of such holistic thinking.

Systems understanding applied to identifying the sustainability impacts of urban water options would first involve the defining of the urban water system that the options would be part of and also the system boundaries. In the urban water context, a systems approach to assessment means that all relevant parts of the water supply chain (supply, wastewater, stormwater) receive adequate attention and that there is an understanding of the interactions at different scales (the allotment, subdivision/suburb and city/region) (Mitchell et al. 2007). Defining the system boundaries will also involve identifying the surrounding systems that could be affected: an urban water system exists within surrounding social, economic, ecological and geophysical systems. A systems perspective can also be utilised in placing boundaries on the analysis in terms of space, timeline and stakeholders.

2.4.2 Estimation and measurement of sustainability impacts

There are two steps to placing a dollar value on sustainability impacts: first, determining the physical magnitude of the impact; second, valuing those physical magnitudes (see Figure 2.2).

Figure 2.2: Identification process suggests two steps in placing a dollar value on source of externality sustainability impacts



Measurement of biophysical changes

Before non-market valuations can be applied, the changes in the biophysical environment that lead to sustainability impacts need to be measured or modelled in physical quantums.

Determining the physical magnitude of a change usually requires either direct measurement or estimates based on some form of modelling using the available physical or biophysical data.

Within the framework of urban water externalities proposed by Bowers and Young (2000), the step of determining the physical magnitude of each externality is seen in terms of the application of a dose–response model: a physical change (the dose) leads to a particular externality (the response). This concept provides a quantitative link from the initial physical impact to the stakeholder affected.

Other assessment techniques available for making the quantitative links from the initial physical impact include:

- life-cycle analysis
- ecological and chemical risk assessment
- energy life-cycle analysis and carbon accounting for GHG impacts.

The importance of quantitative assessment techniques that provide the linkages between the initial impact and the value of the externality needs to be emphasised. A lack of available data or robust estimates of biophysical parameters can be an area of weakness in the economic evaluation of sustainability impacts.

Approaches to economic valuation of sustainability impacts

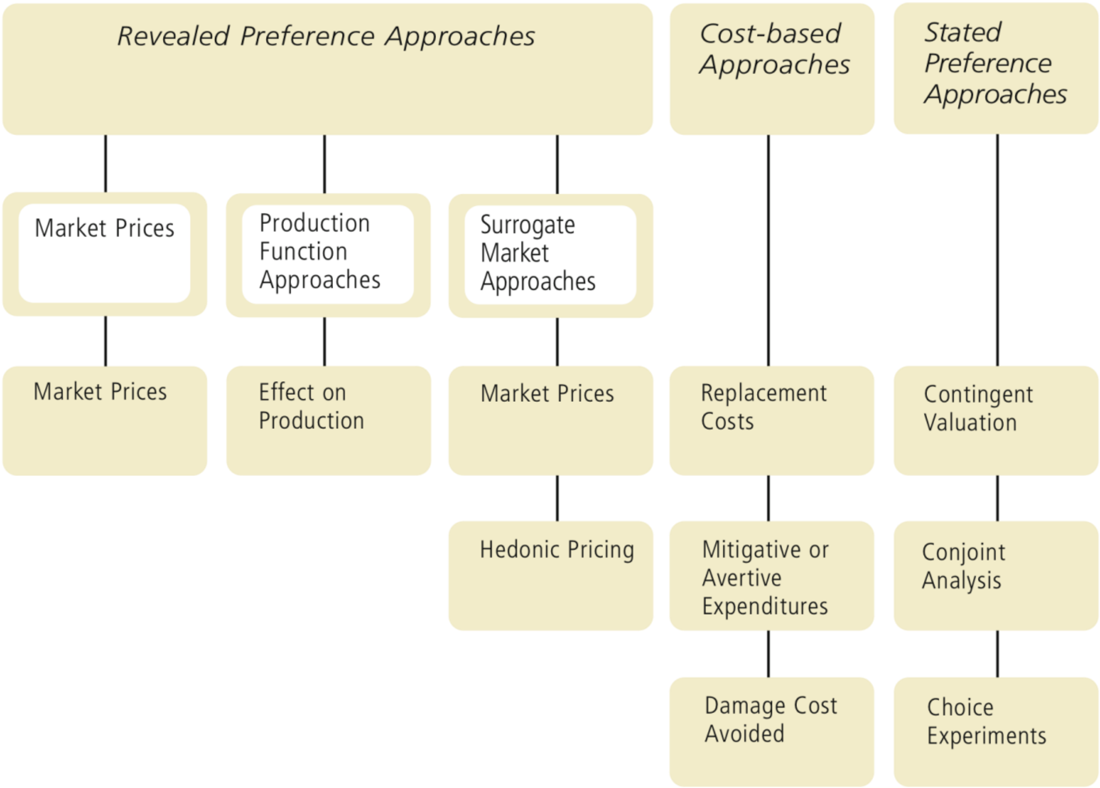
The aim of economic valuation, or putting a dollar value on sustainability impacts, is to determine people's preferences for options and impacts. A wide range of literature exists concerning the techniques available to determine how much people consider various sustainability impacts to be worth. As shown in Figure 2.3, economic valuation methods can be broadly categorised into:

- *market prices methods*: where the prices of marketed goods or services are directly affected, this can be used to value sustainability impacts. Proxy markets may also exist for some impacts (such as to value GHG emissions)
- *production function methods*, which use dose–response relationships to estimate how changes in environmental or biophysical conditions would affect production and the profits from that production
- *surrogate market methods*, which examine the ways in which the effect of sustainability impacts might be indirectly revealed by people's actions in other markets
- *(avoided) cost-based methods*, which include the use of replacement costs, mitigative or aversive expenditures, or damage costs avoided by an option
- *stated preference methods*, which ask consumers to state their preferences directly (for example, how much they are willing to pay to avoid sustainability impacts or whether they are willing to accept them for payment).

An additional approach, benefit transfer, is not a valuation approach per se but involves taking monetary values derived in one context or study and transferring them for use in another context. Benefit transfer can be significantly quicker and less expensive than a new valuation study in the policy situation. However, for benefits transfer to be meaningful, the difference between contexts needs to be considered. Benefit transfer naturally works best when the two sites are similar, when the policy changes/development are similar, and when the valuation procedures at the original study site were analytically sound and carefully conducted (Pearce and Turner 1990). Box 2.4 provides the example of the Cabbage Tree Creek case study, in which benefit transfer and new valuation studies were combined.

Each of these approaches has both advantages and disadvantages, and each has its own resource and time requirements to ensure validity in the estimations of costs and benefits.

Figure 2.3: Classification of valuation methods



Source: Emerton and Bos (2004).

Box 2.4: An example of non-market valuations in options assessment for urban water—the integrated water management investment framework and Cabbage Tree Creek case study

One of the subprojects of the NWC Urban Water IRP project was to develop an investment framework for discretionary expenditure in integrated water management. The framework incorporates direct option costs with non-market valuations of sustainability impacts to give an economic evaluation and comparison of a wide range of water cycle alternatives. These include options principally aimed at alternative supply (rainwater tanks, stormwater harvesting), healthy waterways (water sensitive urban design, streambank rehabilitation) and flood management (purchase of house with high flood-risk). The development of the framework and its application to a case study—Cabbage Tree Creek catchment in Brisbane—was undertaken by Marsden Jacob Associates with Brisbane City Council (BCC).

The investment framework specifically addresses sustainability impacts (water quality, waterway health, recreational amenity etc.) in dollar terms via non-market valuations. Where reasonable, benefit transfer from previous studies is utilised. Where the existing studies could not adequately address Brisbane-specific waterways health and recreation impacts, a new contingency valuation study was commissioned by BCC.

The investment framework involves an initial stage of policy and institutional assessment in order to determine what actions need to be considered within the baseline of existing regulation and which actions represent actual discretionary expenditure. It then involves a two-stage economic evaluation process combining a CBA of integrated water management objectives followed by CEA of options against the priority objectives.

The Cabbage Tree Creek catchment case study was based on an earlier study, which used a multi-criteria approach to options assessment. Key findings from the new economic valuation case study included the following:

- The earlier study recommended a number of investments that were not appropriate for discretionary funding because they were already required under other regulatory tools, planning strategies or service standards.
- The earlier study recommended alternative water supply options; however, the cost of these options in the particular case study area did not exceed the estimated benefits even with local non-market benefits accounted for.
- In this region, investments in waterways health provided the greatest net benefits, and the majority of those benefits were derived from non-market values for environmental protection and recreational amenity (Marsden Jacob Associates 2010a).

The investment framework is relatively generic and could be suitable for use elsewhere. A spreadsheet model developed for the case study is also available and can potentially be adapted to other catchments. Furthermore, one of the two study reports, *Integrated water management investment framework: background, context and technical information* (Marsden Jacob Associates 2010b) contains valuation information collated from available previous studies. The framework, the case study and model, and the collation of information from previous studies should all be useful to urban water planners who are considering the monetary valuation of externalities. These resources can be found at *http://urbanwaterirp.net.au*.

2.4.3 Strengths and limitations of extending CEA via economic evaluation of externalities

The key strength of extending CEA via economic evaluation of externalities is the advantage of incorporating sustainability impacts into options assessments in dollar terms. This allows the sustainability impacts to be compared to direct costs using the single metric of dollars. That metric also communicates the relative value of the urban water direct costs and sustainability impacts to the other costs and benefits of non-water policy goals. Economic evaluation of externalities allows options to be compared on unit costs ($/kL) and portfolios to be compared on their net present value, both with sustainability impacts included.

The key advantage of CEA compared to CBA is that it fits with the existing IRP framework and avoids the issues inherent in valuing urban water service provision.

The inherent limitation of extending CEA via economic evaluation of externalities also relates to the measurement of sustainability impacts in dollars. Although it is technically possible using various methods to calculate a monetary value for any kind of sustainability impact, there will be some types of values that stakeholders, decision makers or the wider community do not consider appropriate to measure and value in dollar terms. Linked to the issue of some impacts being 'intangibles' is the concern stakeholders can have with the idea of 'discounting' future sustainability impacts, as is the practice in economic evaluation (see Box 2.5).

Plant et al. (2007) note that some people find it inappropriate, unethical or absurd to express the value of some impacts in monetary terms. Others argue that monetisation degrades strongly held ethical and moral values, and the variety of widely held motivations and beliefs regarding environmental issues (Hill and Zammit 2000). Stated preference methods such as contingent valuation, in particular, raise concerns when used to derive values for impacts that many consider intangibles. Spash et al. (2005) suggest that the theory underpinning willingness-to-pay studies is inconsistent with empirical evidence and lessons from modern psychology about behaviour and values. For example, it is well known that people are 'loss-averse'—that is, they value gains and losses asymmetrically, which explains the differences between the monetary values they give for willingness-to-pay and willingness-to-accept. Stated preference surveys also result in 'protest bids' from respondents who do not wish to make a trade-off based on monetary valuations of the environment. By excluding those protest bids as anomalies or outliers, an analyst of a stated preference study is implicitly assuming that the rights-based system of values held by the protest bidders is invalid.

One approach to including intangibles in a CEA was suggested by Mitchell et al. (2007). They proposed setting goals or limits for certain types of sustainability impacts and constructing the analysis so that all options must meet those goals. Such an approach is an explicit acknowledgment of the limits of extending CEA via economic evaluation of externalities.

Box 2.5: Issues arising from the discount rate in economic evaluations

The rationale for discounting future streams of costs and benefits is the assumption that individuals prefer consumption now to consumption in the future. The valuation of costs and benefits can be sensitive to the choice of discount rate. For example, applying a higher discount rate results in a more favourable assessment of options if the costs are expected to occur further in the future but the benefits are more immediate.

Discounting has been a topic of some controversy, particularly in the area of sustainability assessment. Although discounting is consistent with economic theory, some critics object to discounting of future costs or benefits on ethical or moral grounds when those costs or benefits represent sustainability impacts. Nevertheless, there is substantial evidence that individuals tend to discount their own future consumption.

A further contentious issue lies in the selection of the discount rate, and whether typically applied discount rates are too high to assess future sustainability impacts. The conventional advice is to select a discount rate that is broadly based on the market rate of return (Harrison 2007). The Australian Government's Office of Best Practice Regulation suggests an annual real discount rate of 7% with sensitivity analysis at 3% and 11% (Australian Government 2007). The office publishes any updates to the suggested rate on its website (*http://www.finance.gov.au/obpr/about*).

However, when attitudes to risk and other factors are taken into account, using such rates may overestimate the true social discount rate of some environmental and natural resources. To illustrate: at a real discount rate of 4%, environmental damage such as climate change 100 years from now would be valued at just one-fiftieth of the value that would be assigned if the damage occurred today. Using another example, at a 7% discount rate, an environmental benefit such as a healthy river in 20 years time has just a quarter of the value it would have today.

The best way to deal with this issue is to test at a range of discount rates, including lower discount rates. Where the ranking of options is sensitive to the choice of the discount rate, that should be highlighted for decision makers.

2.5 Options and portfolio analysis using MCA

MCA as a framework for decision making does not try to attribute dollar values to environmental or social impacts; instead, this approach involves using participatory processes of some form to rate each option against selected decision criteria. As Lundie et al. (2008a:10) are careful to note, the use of an MCA framework '*does not inherently lead to a sustainable decision*'. Rather, it is the adoption of criteria that value sustainability as an outcome, along with the participation of stakeholders in the process, which can assist in making decisions that are more sustainable than those made on a business-as-usual cost-only basis.

In a sustainability assessment, MCA will involve initially selecting the assessment criteria so as to cover the potential impacts on sustainability, and then designing and implementing appropriate processes to rate each option against the criteria. The decision-making metric in MCA is usually a normalised score for an option across each of the criteria. Normalisation converts criteria results, which may be qualitative or quantitative, with varying units, into a uniform dimensionless number for further analysis. Normalised scores can then be left to stand alone or they can be aggregated using a weighting process into a single index or multiple indexes. An example of using multiple indexes might be a study with 'triple bottom line' scoring for economic, social and environmental impacts.

MCA is a wide field, and numerous potential methods and techniques have been presented in the literature. This can be a problem for practitioners new to MCA. For an overview of the use of MCA for policy problems, the *Multi-criteria analysis: a manual* published by the United Kingdom Department of Communities and Local Government (DCLG 2009) offers useful advice. The manual provides a broad overview of MCA techniques for non-specialists, as well as more detailed step-by-step guidance in applying a multi-criteria decision process to a specific decision-making problem.

While *Multi-criteria analysis: a manual* provides excellent general guidance, more specific guidance in multi-criteria decision processes applied to sustainability in urban water planning in Australia is covered by the WSAA sustainability framework (Lundie et al. 2008a). The WSAA framework lays out a step-by-step procedure that focuses on opportunities for stakeholder involvement and aims to be applicable to decision making at a wide range of project scales. The framework provides detailed guidance on the many methodological decisions encountered in fitting the MCA approach to a particular decision-making context. Lundie et al. (2008a) also stress that the participation of stakeholders in the process is key to advancing sustainability. Both the DCLG (2009) and Lundie et al. (2008a) are included in the list of further resources on MCA in Section 2.8 at the end of this paper.

The material covered in this section includes the identification of sustainability impacts for urban water options, the selection of relevant criteria, the measurement of those impacts, and an introduction to MCA techniques for discriminating between options. A subsection then addresses the question of how MCA might be utilised within the existing IRP framework. The section concludes by outlining some of the strengths and limitations of an MCA approach.

2.5.1 Identifying sustainability impacts

Incorporating sustainability into an MCA decision-making framework requires the designer of the process (in this case, a water planner) to give 'adequate attention to frame the problem and objectives for its solution [from a sustainability perspective] so that all stakeholders are willing to buy into and hence be able to achieve the broader policy goal of sustainability' (Lundie et al. 2008a:18).

Once decision objectives are agreed to, they need to be translated into specific and measurable criteria for assessing the consequences of each option. The DCLG (2009:32–39) provides detailed guidance on identifying criteria and subcriteria. The DCLG (2009:58) also gives guidance on organising criteria by clustering them under higher and lower level objectives in a hierarchy. The DCLG argues that, as well as providing clarity, this structuring can lead to better criteria by highlighting conflicts and overlaps between criteria.

In many cases the objective of the study may be relatively broad, for example, 'minimising the economic, environmental and social cost of the urban water options selected'. In such cases, a good way of incorporating the range of sustainability impacts into the MCA process is to start with a generic set of sustainability criteria for urban water. Those criteria can then be adapted to suit the specific circumstances of the decision to be made.

Sets of sustainability criteria for urban water have been defined by various authors. Considering the needs of the Australian water industry, Lundie et al. (2008a) provide examples of primary and secondary criteria for sustainability assessment in terms of economic, human health, environmental, technical and social criteria (see Table 2.3). In an earlier guide for the British water industry, Ashley et al. (2004) also defined a set of economic, environmental, technical and social criteria. Alternative sets of sustainability criteria for urban water can be found in the literature, for example Hellström et al. (2000) and Balkema et al. (2002).

The identification of externalities by mapping them from their source through to the stakeholder who is affected (as shown in Figure 2.1) could also be used to help define sustainability criteria in a specific situation. The big difference, however, is that sustainability criteria can be defined at the source of the impact (Step A) or the change in the environment (Step B) if determining the impact on stakeholders (Step C) is too difficult.

Whether the investigation starts from a generic set of sustainability criteria or develops them from scratch, the criteria should ideally be based on a systems understanding of urban water (as described in Section 2.2.3 in terms of a characteristic of good practice and expanded in Section 2.4.1). This involves seeking to establish the potential impacts of alternative options on the urban water system and surrounding systems.

Once criteria have been selected, a process is then needed for scoring each option against the criteria.

Table 2.3: Primary and secondary criteria

Primary criteria	*Secondary criteria*
Economic	Life-cycle capital expenditure
	Life-cycle operational expenditure
Human health	Risk of infection (DALY—e.g. years of life loss)
	Exposure to harmful substances (e.g. toxic, carcinogenic or endocrine-disrupting substances)
Environmental	Extraction of fresh water and groundwater
	Land-use disturbance
	Resource input [t/year]
	Biodiversity
	GHG emissions
	Eutrophication [potential]
	Photochemical oxidant formation
	Ecotoxicity [potential]
Technical	Performance (potable water and wastewater quality)
	Reliability
	Resilience/vulnerability
	Flexibility
Social	Affordability
	Employment generation
	Acceptability to community
	Distribution of responsibility
	Organisational capacity and adaptability
	Public understanding and awareness

Source: Lundie et al. (2008a).

It is useful to note that Lundie et al. (2008a) include equity concerns such as affordability, governance concerns such as distribution of responsibility and organisational capacity, and technical concerns such as performance in their suggested criteria. These concerns would not be directly represented in an extended CEA framework. However, affordability issues are handled in the existing IRP framework in terms of a 'cost test' for customers. Some technical concerns such as the relative performance will also come up elsewhere in the IRP framework. Section 2.5.4 addresses the question of how MCA might be utilised within the existing IRP framework.

2.5.2 Measuring sustainability impacts of options

As outlined in the WSAA sustainability framework (Lundie et al. 2008a), performing a detailed assessment of each option in order to generate normalised criteria scores is a three-step process:

1. Generation of a performance matrix
2. Normalisation of performance scores
3. Weighting for primary and secondary criteria.

These steps and the methodological decisions involved are discussed in detail in the WSAA sustainability framework. The steps are expanded on briefly below to introduce the approach and enable comparison with the CEA framework.

The physical measurement of impacts

Physical impacts are measured or estimated and a 'performance matrix' is generated. The quantitative assessment techniques used to physically measure or model sustainability impacts as part of valuing externalities in a CEA framework (see Section 2.4.2) can also be used to provide data on impacts covered by criteria in the MCA framework. However, one advantage of using an MCA framework is that it can also incorporate qualitative assessments of sustainability impacts where physical data is unavailable.

With an assessment based on sustainability criteria, it may be sufficient to demonstrate the linkages between the impact of an option and a measurable indicator. Depending on systems boundaries, MCA does not always explicitly identify which individual or group is affected, unlike in the externalities approach. (This is addressed in Section 2.5.1 with references to Figure 2.1.) For example, rather than demonstrating that reduced sediment pollution in a river due to reduced pumping will improve bass fishing for anglers by a specific amount through a linkage of pollution load to macro-invertebrate numbers to bass numbers to anglers, an MCA criterion could simply be the level of total suspended solids released to waterways due to various options, with the implicit qualitative knowledge that this had associated benefits for bass fishing.

Lundie et al. (2008a:37) recommend deciding upon one level of depth for assessment of all options and criteria under study where possible. However, they acknowledge that in practice such consistent data quality may not be available. If that is the case, they recommend that differences in data quality and uncertainty be flagged in the final reporting document.

Normalisation of performance scores

The indicator results for each criterion should be normalised (with regard to a reference point) before ranking the criteria and/or adding weighting factors to them. The main aim of normalisation of criteria results is to better understand the relative importance and magnitude of their effects. Normalisation converts the criteria results with their varying units into uniform, dimensionless numbers for further analysis.

Three approaches to normalisation are outlined in the WSAA framework: the min–max approach, the ranges approach, and the distance to target approach.

Weighting for primary and secondary criteria

Criteria-based approaches as used in practice can be characterised according to their methodology for criteria score aggregation. Processes used for aggregation include those that aggregate criteria scores into:

- a single index using a form of weighted sum aggregation, such as the Gold Coast Waterfutures project (Lundie et al. 2008b)
- multiple indexes (economic, social, environmental, technical etc.), by keeping cost and other criteria separate for assessment alongside one another, such as in the Eurobodalla IWCM Strategy (DPWS 2003).

Regarding aggregation, Lundie et al. (2008a:46) recommend that, if criteria scores are to be aggregated into a single score, that should occur during the final decision-making stage so that decision makers can access both levels of results and understand the aggregation process.

They argue that aggregating scores into multiple indexes (which they call primary criteria) is preferred if the total number of primary criteria is relatively small. If there are many indexes, they argue that a form of weighted sum aggregation should be performed so that the value preferences underlying the decision are transparent to observers. They note that the shortcoming of aggregating scores into a single index is that it:

> assumes that all criteria scores are directly substitutable. This assumption is rarely held in environmental projects (e.g. that a project that is highly flexible may cancel out a bad performance in risk of infection), which is a shortcoming of this simplified methodology (Lundie et al. 2008a:46).

In the wider MCA literature, there are various formal MCA techniques that attribute relative weights to criteria in order to differentiate between options. The DCLG (2009) gives a broad overview of the full range of MCA techniques, including direct analysis of the performance matrix; multi-attribute utility theory; linear additive models; the analytical hierarchy process; outranking methods; procedures that use qualitative data inputs; MCA methods based on fuzzy sets; and other less common MCA techniques.

2.5.3 Using MCA as part of the existing IRP framework

This section addresses the question of how MCA might be utilised within the existing IRP framework. In doing so, it also considers how the IRP framework and the sustainability framework described by Lundie et al. (2008a) might be used together in selecting a group of options as part of a long-term urban water strategy for a region.

As a starting point, there are several decision points where MCA techniques could be used:

1. The first screen-level assessment of options
2. Comparing and ranking options
3. Developing alternative portfolios
4. Comparing portfolios.

These various decision points are considered below.

Screen-level assessment of options

If used only to remove particularly poor performers (a first screen-level assessment), an MCA before a CEA could be beneficial. This would involve using the MCA to limit the options that are included in the CEA. The approach has similarities to the potential way of treating intangibles in a CEA discussed in Section 2.4.3.

Comparing and ranking options

Using MCA to directly rank options is an approach likely to be inconsistent with the IRP framework. This is because if an MCA is used to compare and rank options then it will be particularly difficult to maintain the IRP objectives associated with 'least cost' and thereby demonstrate that the final strategy is cost-effective. Another IRP principle is equal treatment of demand- and supply-side options. If MCA is used for options assessment, there is a danger that highly cost-effective demand-management options may be missed if only water conservation options popular with stakeholders, such as reuse and rainwater tanks, are compared to large-scale supplies.

Developing alternative portfolios

Starting from the existing IRP framework, White et al. (2008) suggest using MCA in a participatory approach to create portfolios. The IRP process outlined in the *Guide to demand management and integrated resource planning for urban water* (Turner et al. 2010) shows how to combine options into a single least-cost portfolio, but it does not show how multiple portfolios might be constructed. In this method, portfolios are created by modification of the least-cost portfolio based on environmental, social and technical indexes using multiple criteria. MCA techniques are used to screen in and out individual options from the least-cost portfolio. This creates a number of new portfolios that have different characteristics (for example, with the poorly performing options on the environmental, social or technical index excluded). Those portfolios could then be compared to the least-cost portfolio on net present value.

Comparing portfolios

Lundie et al. (2008a) illustrate the sustainability framework using the example of a hypothetical town planning for long-term future water needs. This aims to show that the step-by-step approach to multi-criteria decision-making is applicable to decisions of this scale. The hypothetical planning situation uses MCA to decide between four 'water future scenarios', each with different options. The development of portfolios of options for the water future scenarios is not addressed in the example. This issue is noted by Carden (2006), who examined the possibility of using the Lundie et al. framework for urban water planning in south-east Queensland. While Carden found the framework appropriate for the many different objectives in that region, it did not help to answer the question of how to develop portfolios of options.

One approach that could be taken is to develop a number of different portfolios for a water strategy, each of which meets slightly different objectives. Each portfolio would be developed based on the IRP process outlined in Turner et al. (2010) and each would meet the primary objective of securing water supplies. Different portfolios would also meet different secondary objectives. For example, one portfolio might meet a wastewater reuse target, a second might provide drought-proof water supplies to key recreation fields, a third might improve stormwater quality and a fourth might meet all of those objectives. The portfolios could then be compared on net present value, and an MCA approach could be used to select between them.

As Lundie et al. (2008a) illustrate, using MCA to compare portfolios can make sense. This is because portfolios can be compared on net present value together with other criteria. Alternatively, as White et al. (2008) show with their methodology for developing alternative portfolios within an IRP framework, MCA can be utilised in developing alternative portfolios. Furthermore, using MCA for a screen-level assessment before CEA may also be helpful in some situations.

2.5.4 Strengths and limitations of using an MCA framework

The key strength of MCA is that it explicitly acknowledges that complex decisions are rarely made by one person or on the basis of a single metric. MCA recognises that decision making may involve multiple objectives and multiple viewpoints, and that trade-offs will need to occur between objectives. The DCLG (2009:21) argues that MCA is preferable to less formal decision-making unsupported by structured analysis for the following reasons:

- It is open and explicit.
- The alternative criteria that any decision-making group may select are open to reanalysis and to change if they are felt to be inappropriate at a later date.
- Scores and weights, when used, are also explicit and are developed according to established techniques. They can also be cross-referenced to other sources of information on relative values, and amended if necessary.
- Performance measurement can be subcontracted to experts, and so need not necessarily be left in the hands of the decision-making body.
- MCA can provide an important means of communication within the decision-making body and sometimes, later, between that body and the wider community.
- When scores and weights are used, they also provide an audit trail.

For advocates of MCA, a further strength is its potential for stakeholder participation in both the selection and the valuation of criteria. Participation is central to the sustainability framework outlined by Lundie et al., who describe moving towards sustainability in urban water as requiring ‘a paradigm shift among all water users’ (2008a:14) that is both cognitive and behavioural. From this viewpoint, stakeholder participation throughout the assessment process is very important because it ‘forms part of a broad mobilisation of understandings and practices among both users and providers’ (Lundie et al. 2008a) regarding the potential for sustainable water planning.

A key limitation of MCA approaches is their reliance on good criteria selection and the risk that interrelationships between criteria can lead to double counting. For example, paradoxically, some water industry practitioners have noted that MCA decision frameworks commonly lead to traditional water and wastewater solutions, instead of leading to *a paradigm shift* in water planning. This is likely to be because non-traditional alternatives will tend to score poorly on a range of criteria such as ‘technical risk’, ‘organisational capacity’ and ‘social acceptability’, which are all linked to the alternative’s novelty.

Caution should also be applied in the treatment of cost as a criterion. In his criticism of MCA, Bennett (2005:258) singles out a concern about weights being used to combine values for market (costs) and non-market criteria. There is a possibility that the inclusion of costs in this way may double count other impacts that are already factored into the cost assessment, such as the costs of meeting health regulations. For this reason, the DCLG (2009) offers guidance on assessing the rigour of the selected criteria. The final list of criteria should be assessed for completeness, avoiding redundancy, operability, double counting, conciseness and scale (for example, including impacts that occur over time).

While stakeholder involvement in the selection of criteria is seen as a strength by some, it leads to the potential for stakeholder gaming of the selection of criteria, as discussed in Section 2.3.1. While gaming can be a problem in any assessment that involves stakeholders in scoring or valuing impacts, in MCA stakeholder involvement in selecting criteria can create a tendency to use criteria that overlap and do not form a coherent set. This problem arises due to pressure to meet the interests of particular stakeholders who want to see 'their' criteria represented, even if the sustainability impact is covered by existing criteria. Some critics argue that MCA is illegitimate precisely because of the participation of stakeholders in the design of the framework of analysis (Bennett 2005). Such criticisms tend to come from strong advocates of CBA. However, as is discussed in Section 2.3.1, care is needed in structuring any stakeholder participation, whether for CBA, CEA or MCA.

2.6 Incorporating the results back into the planning process

This section outlines the issues that need to be considered when integrating the results of sustainability assessments back into an urban water planning process. It covers the important issues of analysing and communicating the level of uncertainty that exists within the results of a sustainability assessment. It also raises the need for transparency in reporting, particularly in relation to trade-offs that are made between sustainability impacts when assessing options for urban water.

2.6.1 Treatment of risk and uncertainty

When planning for urban water service provision, decision makers are faced with many unknowns, both current and future. It is not possible to know with certainty the influence of factors such as population growth, weather, climate, industry demand, people's behaviour and responses, or people's attitudes and values. Assessment of sustainability impacts introduces further factors. Uncertainties may exist in each link in the chain, from an option as a potential source of an impact to valuing a particular externality or sustainability criteria. Some of these unknowns are quantifiable, and there are risk assessment methods for them. However, it is likely that significant uncertainty will remain in the measurement and valuation of some impacts.

It is good practice to separate those uncertainties that can be dealt with via risk assessment from other forms of uncertainty where the unknowns are greater. The differences between 'risk' and other forms of 'uncertainty' have been detailed elsewhere (Wynne 1992, Mitchell et al. 2007). Put simply, the concept of risk can be applied to situations in which probabilities can be assigned or quantified, whereas uncertainty relates to unknowns that cannot currently be measured or reasonably estimated.

Risk can be addressed analytically because both the magnitude and the probability of impacts are known or can be estimated. Common methods for the analysis of risk are Monte Carlo analysis and Bayesian approaches. The distinction between risk and uncertainty is not a precise one because there are degrees of subjective judgment about whether unknowns can be quantified or estimated. For example, risk assessment commonly rests on assumptions that future probabilities will replicate past patterns, or that the expert judgments used in Bayesian approaches are reasonable estimates.

Where probabilities, magnitudes or both are simply not known and cannot be estimated, 'real uncertainty' exists. Some types of real uncertainty can be dealt with analytically by conducting sensitivity analyses or scenario analysis. But for those analyses to be meaningful, an understanding of the boundaries of that uncertainty is necessary. For scenario analysis, an understanding of how uncertain parameters are correlated is also required. In the end, if even the boundaries of an uncertain parameter are not known, then the only option for an analyst is to acknowledge the uncertainty.

How to treat uncertainty and risk is an important consideration for any analysis, particularly one such as a sustainability assessment. The danger is that taking a deterministic view and omitting the mention or analysis of uncertainty and risk from the assessment could lead to conclusions that do not take into account society's preferences and attitudes towards uncertainty. More specifically, failing to acknowledge the uncertainty about key decision variables will lead to decision makers having a false idea of the degree of precision involved in an analysis and its results.

By analysing uncertainty where possible, and then acknowledging the uncertainty that remains in their results, water planners do what they can to promote the best environmental, economic and social outcomes. Furthermore, where uncertainty exists there is always the potential to obtain more information for future analysis, and that is recommended. The potential may also exist to design an adaptive management response that allows for flexibility and is adjusted as time passes and more data or information comes to light.

2.6.2 Transparent reporting

Irrespective of the choice of sustainability frameworks and methods, clear and comprehensive reporting of the sustainability assessment process is crucial to ensuring transparency of the overall decision process. Transparent reporting seeks to present the objectives, assumptions, methods and uncertainties in a coherent and systematic way. The appropriate level and presentation of detail will depend on the intended audience (Mitchell et al. 2007), but all reports should provide sufficient information, either in appendixes or in links to other reports, for someone else to be able to replicate the analysis.

For sustainability assessment, a critical aspect of transparency is to show how values have been assigned to impacts, and therefore how environmental, social and economic impacts have been weighed against one another. Ideally, transparency in valuation will go further, demonstrating what trade-offs have been made between different sustainability impacts and between sustainability impacts and direct costs for specific options. Transparency should also mean acknowledging whose values (stakeholders, survey participants etc.) and what type of values (consumer or financial values in a CEA, stakeholders' or citizens' interests in an MCA) have been included in the sustainability assessment.

With an extended CEA framework, it is critical that monetisation of externalities is conducted in a way that is transparent, and that the methods and assumptions used (and the consequences for the degree of certainty of the results) are made explicit. An extended CEA framework should also acknowledge the existence of impacts for which no meaningful monetary valuation was deemed possible.

Many weighting techniques exist in MCA, and the detail of the processes can potentially obscure the overall framework, so it is important to state whose values are being incorporated and why. In MCA, techniques vary in the way they incorporate criteria, the application and weights given to criteria, the mathematical algorithms used, the structures used to describe preferences, the level of uncertainty embedded in the process and the opportunity for stakeholders to participate (Dodgson and Spackman 2000).

It is important to be explicit about the assumptions that are embedded in the valuation method chosen. This allows both the analyst and a reviewer to consider whether the valuation method is consistent with the stated goals of the decision-making process.

For any sustainability assessment, a transparent report should include:

- the *objectives and context of the study*, including how the assessment informs the overall decision, and the system boundaries (space, time and stakeholders)
- the *key assumptions*, including evidence of their validity
- *research and analysis methods*, including data sources, approaches to obtaining data (including stakeholder consultation and participation), and valuation methods used (justification of the methods chosen might include detailing of resource constraints, but an assessment of the overall validity of the results is still required)
- *uncertainty analysis*, clearly documenting how ranges and probabilities affect the results and recommendations.

Transparent reporting is important because it allows organisations that are making decisions about investments of public money for urban water outcomes to demonstrate, and be held to account for, the reasons for those decisions. Transparency in reporting is a key application of corporate social responsibility principles, which are often found in the enabling legislation and strategic direction statement of water authorities and other organisations undertaking urban water IRP (Mitchell et al. 2007). More generally, it is important in order to ensure the credibility and defensibility of the recommendations and results of the sustainability assessment and of the broader water planning process.

In this relatively new area, comprehensive and publicly available reporting of sustainability assessments in the urban water planning field will also make a significant contribution to the information and knowledge base of the Australian water industry.

2.7 Conclusions

This resource paper has discussed two broad assessment frameworks: extending CEA via economic evaluation of externalities and MCA. It has examined methods for using those frameworks to inform urban water planning. It has aimed to fill some of the more significant gaps that exist in sustainability assessment in urban water, particularly in relation to options and portfolio assessment in IRP studies. This has meant providing water planners with enough background on how to incorporate sustainability impacts into water planning so that they can make decisions about which methods best suit their situations and take the next steps towards conducting sustainability assessments of options for urban water.

The paper has set out six common steps that should be discernible in any sustainability assessment of options for urban water:

1. Drawing boundaries and establishing a baseline
2. Recognising that there are impacts of options not represented in the analysis of direct costs that require further assessment
3. Identifying the impacts to include in a broader assessment
4. Estimating the magnitude of each impact
5. Placing a value on each impact
6. Interpreting and communicating the results.

The paper has also set out the characteristics of good practice:

1. An approach aligned with the governance situation in the region
2. A structured assessment framework
3. A method appropriate to the circumstance and scale of the decisions
4. The application of a systems understanding when identifying impacts
5. The use of robust estimates of the magnitude of impacts
6. Clarity in the treatment of uncertainty
7. Transparent valuation and reporting.

These six common steps and seven good practice characteristics can be used together as initial checklists when planning a sustainability assessment of urban water options and then as a check throughout the process as the inevitable iterations occur.

In conclusion, conducting a sustainability assessment of urban water options and incorporating the results faithfully into decision making is always likely to be difficult work due to the varied objectives and stakeholder interests involved. It is, however, important work. Ideally, the outcome of a sustainability assessment will be a plan for an urban water system that has all the characteristics of good practice and can be implemented with the support of the local community because it reflects their values. Finally, this is an emerging field with a limited pool of comprehensively documented examples. The authors encourage practitioners to share their experiences with others in the profession.

2.8 Resource list

This section lists key resources for further information on this topic. References for this paper not included in this list are provided in the Section 2.9.

2.8.1 State-based urban water planning guidelines

IWCM resources are at *http://www.dwe.nsw.gov.au./water_urban/utilities_cycle.shtm*.

Victoria has regional ‘sustainable water strategies’ that plan for long-term water supply across Victoria. See *http://www.ourwater.vic.gov.au/programs/sws*.

2.8.2 Water industry guidance documents

Ashley R, Blackwood D, Butler D and Jowitt P (2004). *Sustainable water services: a procedural guide*, IWA Publishing, Milton Keynes, United Kingdom.

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2.8.3 Guidance on economic analysis

Bowers J and Young M (2000). *Valuing externalities: a methodology for urban water use*, CSIRO Urban Water Program, CSIRO Policy and Economic Research Unit, 45.

Queensland Treasury (2002). *Guidelines for financial and economic evaluation of new water infrastructure in Queensland,* Queensland Government.

NSW Treasury (2007), *Guidelines for economic appraisal*, Office of Financial Management, NSW Treasury.

United States Environmental Protection Agency (2008). *Guidelines for economic analyses*, EPA Science Advisory Board, latest revision EPA 240-R-00-003 September 2000 and latest update September 2008 draft, available at *http://yosemite.epa.gov/EE/epa/eerm.nsf/vwRepNumLookup/EE-0516?OpenDocument*.

2.8.4 Guidance on multi-criteria analysis

DCLG (Department of Communities and Local Government) (2009) *Multi-criteria analysis: a manual*, DCLG, available at *http://www.communities.gov.uk/publications/corporate/multicriteriaanalysismanual*.

2.8.5 Resources for public participation

Carson L (2008). ‘The IAP2 spectrum: Larry Susskind in conversation with IAP2 members’, *The International Journal of Public Participation*, 2(2).

IAP2 (International Association for Public Participation) (2007). *IAP2 spectrum of public participation*, IAP2, available at *http://www.iap2.org/associations/4748/files/spectrum.pdf*.

2.8.6 Examples of urban water planning applications of multi-criteria analysis

DPWS (Department of Public Works and Services) (2003). Eurobodalla Integrated Water Cycle Management Strategy, DPWS, Sydney.

White S, Fane S, Giurco D and Turner A (2006). 'Putting the economics in its place: decision making in an uncertain environment', *Ninth Biennial Conference of the International Society for Ecological Economics*, New Delhi, India, available at *http://www.isf.uts.edu.au/publications/Whiteetal2006economicdecisionmaking.pdf*.

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Water Corporation (2008c). *Water Forever: sustainability assessment*, Water Corporation, available at *http://www.thinking50.com.au/go/publications*.

2.8.7 Examples of urban water planning applications including the monetisation of externalities

Hatton MacDonald D, Barnes M, Bennett J, Morrison M and Young M (2005). 'Using a choice modelling approach for customer service standards in urban water', *Journal of the American Water Resources Association*, 41:719–728.

Marsden Jacob Associates (2010a). *Integrated water management investment framework: framework summary and case study for Cabbage Tree Creek*, prepared for Brisbane City Council and the National Water Commission.

Marsden Jacob Associates (2010b). *Integrated water management investment framework: background, context and technical information*, prepared for Brisbane City Council and the National Water Commission.

The two reports and other resources from the integrated water management investment framework and Cabbage Tree Creek case study can be found at *http://urbanwaterirp.net.au*.

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Australian Government 2007, *Best practice regulation handbook*, Canberra.

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Dwyer G, Douglas R, Peterson D, Chong J and Maddern K 2006, 'Irrigation externalities: pricing and charges', ISF staff working paper, UTS Sydney.

Dodgson J and Spackman A 2000, *Multi-criteria analysis: a manual*, Department of the Environment, Transport and the Regions, London.

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3. Complementary analytical techniques for urban water forecasting in IRP

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Summary

What is the purpose of this paper?

A key aim of the Australian IRP framework described in the *Guide to demand management and integrated resource planning for urban water* (Turner et al. 2010) is to ensure that water service providers forecast water demand as accurately as possible for their specific region, taking into consideration available resources such as staff time and data availability. Combined with a detailed knowledge of the yield, this helps to clarify the supply–demand gap for a specific area, ultimately assisting decision makers, as part of their strategic planning, to determine the best portfolio of options to fill the supply–demand gap in the coming years.

The *Guide to demand management and integrated resource planning for urban water* (Turner et al. (2010) details how to forecast water demand using a hybrid sector and end-use based analysis, which is considered best practice internationally and is currently being used by leaders in the Australian water industry. However, to successfully undertake this form of analysis, various other techniques should also be used to ‘unpack’ how historical water demand has been affected by various factors and how those factors should be considered in demand forecasting.

The purpose of this resource paper is to examine the various other techniques available for urban water demand analysis. It aims to provide existing and potential users of the Australian IRP framework, the associated explanatory *Guide to demand management* (Turner et al. 2008b) and the updated *Guide to Demand management and integrated resource planning for urban water* (Turner et al. 2010) with a broader understanding of the various analytical techniques available to inform detailed demand forecasting.

Why is the paper needed?

Demand forecasting is required by every urban water service provider in Australia, whether a large coastal water utility responsible for millions of people or a small council providing services to inland remote communities. In either case, the water service provider needs to project how much water must be provided over the coming years in order to service those needs.

Many water service providers are now recognising the importance of understanding how water is used and that sector and end-use based analysis methods are the key. Details to aid analysts on how to conduct sector and end-use based approaches are provided in Turner et al. (2010).

There are a wide range of other analytical techniques available to further unpack historical demand. Some techniques are more useful than others in informing demand forecasting, some need significant amounts of data and data processing, and others require an in-depth understanding of statistics to enable interpretation. While there is significant literature on these other techniques, there is no single place to obtain an overview of the range of techniques available, examples of their use, their potential limitations, or guidance on which techniques make sense to use. This paper aims to fill that gap.

Will this paper be useful to me?

The resources developed as part of the NWC Integrated Resource Planning for Urban Water project are intended to aid those individuals in the water industry focused on urban water planning and management. This audience is very broad, ranging from large water utilities dealing with billions of dollars of investment to small councils potentially with limited resources, skills or both. The resources developed as part of this project generally aim to focus on the core group of organisations and practitioners in the middle of that spectrum.

Hence, the intended audience for this resource paper is those individuals and teams responsible for water service provision and management who are involved in demand forecasting. That group will have varying knowledge and skills in demand forecasting using sector and end-use analysis and the complementary techniques identified in this paper. Therefore, this paper aims to provide both a broader and a deeper perspective on analytical techniques available and how they can be useful to demand analysts. Many of those responsible for demand forecasting may contract out all or part of the task, so this paper also aims to provide sufficient background on the various techniques available for them to engage more effectively with the package of work contracted and the resulting output.

Where to look in the paper?

This resource paper contains 10 main sections, of which seven are dedicated to addressing different types of analyses of urban water demand. Each section addresses the various techniques used, provides examples of their application and common pitfalls and analytical limitations with, where available, potential solutions.

- Section 3.1 provides an overview of the current challenges in demand forecasting, the key techniques considered in the paper and a summary of how they can best be used by water practitioners.
- Section 3.2 examines the modelling techniques used in correcting demand for weather and climate effects (climate correction).
- Section 3.3 provides guidance on analysing water demand data to identify trends.
- Section 3.4 looks specifically at the techniques employed to distinguish base and seasonal demand from available demand data.
- Section 3.5 covers forecasting of near-term and seasonal demand peaks.
- Section 3.6 reviews the various methods employed for determining price and other elasticities (econometric estimation).
- Section 3.7 looks at demand analyses performed through the lens of demographic and land-use information.
- Section 3.8 looks at attempts to incorporate behavioural responses to water planning policy into demand forecasting.

- Section 3.9 considers how the complementary analytical techniques described in the paper should be incorporated in integrated resource planning (IRP) demand forecasting.
- Section 3.10 provides references.

All readers are advised to read the summary and Section 3.1 for an overview of why they need to read this resource paper and the specific techniques discussed. Section 3.1 includes a summary table of the approaches and techniques, which gives guidance on which technique may be of most use under particular circumstances—for example, demand analysis and forecasting as part of a strategic plan conducted by a mid-size utility as a rapid appraisal with limited time and budget, versus a detailed supply–demand plan conducted by an experienced large utility that already has a detailed sector and end-use demand forecasting model. Having this overview, the reader can then delve into specific sections to gain a deeper insight into the techniques of interest.

Scope of the resource paper

Some of the techniques identified are already used by practitioners in the water industry. Some come from other disciplines and may or may not be useful to unpack how water is used and therefore ultimately how demand can be forecast. Hence, this paper aims to identify many of the key techniques available for analysing water demand, provide examples of their application, explore how they could be used to aid demand analysis and forecasting, and clarify some of their key strengths and weaknesses.

The paper considers empirical analysis techniques that can be used to inform and support the sector and end-use based forecasting described in Turner et al. (2010). End-use modelling and other deterministic methods are explained in detail in the guide and are therefore not covered in this paper.

What are the take-home messages?

Water demand analysis and forecasting are conducted by all water service providers across Australia with varying degrees of rigour. It is now recognised that an appreciation of historical demand is essential to all levels of planning, from operational to strategic planning, and that conventional forecasts that do not take into consideration the range of factors that influence demand are no longer appropriate. This paper is designed to aid practitioners in understanding and adopting analytical techniques that may be useful in unpacking how water has been used in their service area to then inform demand forecasting.

3.1 Introduction

3.1.1 Current challenges in demand forecasting

Urban water usage in Australia is continually changing due to increased attention to system leakage and pressure management; changing customer behaviours; new appliances and technologies in both the residential and the non-residential sectors; alternative water supplies; and other key drivers, such as population growth and urban consolidation. In addition, recent droughts affecting many cities and regional centres across the country led to the application of water restrictions in many regions and the implementation of major demand management and source substitution initiatives. Those initiatives will have affected demand, but it is often uncertain to what extent, especially in the case of restrictions for which ‘bounce back’ (demand returning to pre-restrictions levels once restrictions have been lifted) has been observed in the past.

With these dynamics in play, the task of developing an understanding of the following questions is becoming increasingly complex:

- How has water been used historically and how is it being used now?
- How can we more accurately forecast water demand (to understand the supply–demand balance into the future)?

- How can we design programs to tap into the conservation potential and fill the supply–demand gap?

3.1.2 Primary demand forecasting methods

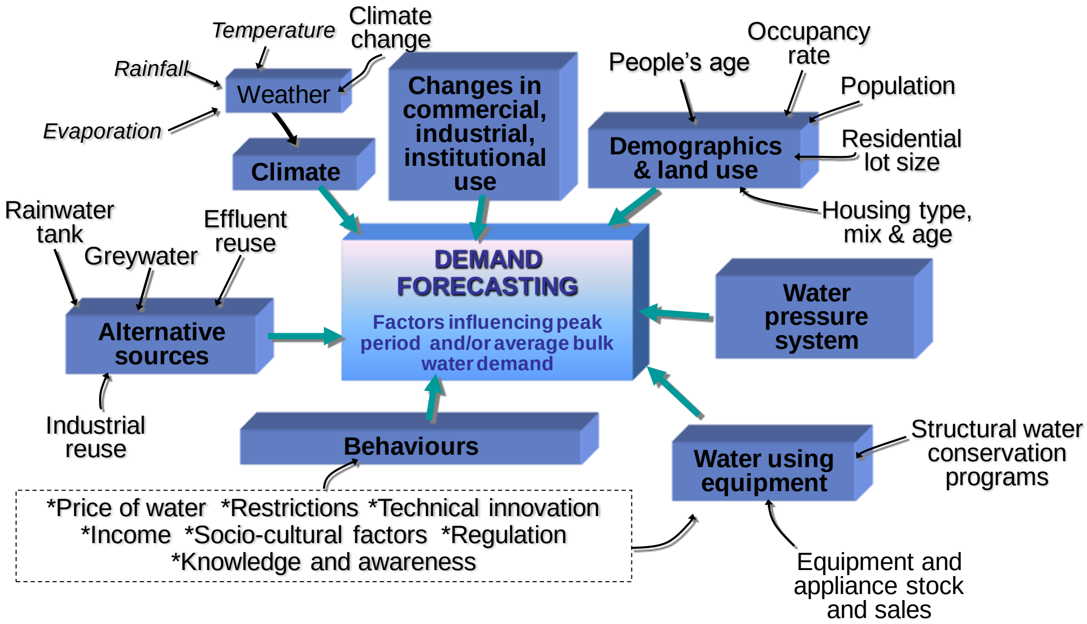
The primary methods used for water demand forecasting include:

- The simple litres per capita per day (LCD) method of analysing historical bulk (aggregated) water demand to determine an overall LCD figure, which is then multiplied by the projected population. In more recent times historical demand is occasionally corrected for the influence of climate and weather using various regression techniques to obtain a 'climate neutral' average LCD demand for forecasting (as discussed in this paper).
- A sector-based approach, which at minimum investigates residential demand (single and multiresidential properties), non-residential demand (commercial, industrial and institutional sectors and subsectors) and non-revenue water (real and apparent losses). With a better understanding of how water is being used, demand is then projected according to population growth or other sector-specific base units (for example, the number of properties or utility accounts, employment, floor space), as deemed appropriate.
- An end-use analysis, which uses a 'bottom-up' approach to explain historical demand (predominantly in the residential sector) associated with typical end uses such as toilets, washing machines and evaporative air conditioners. The demand for that end-use is translated into aggregate demand by multiplying an individual end-use demand by frequency of usage, projected demographic growth (population, single and multiresidential dwelling numbers, and occupancy as appropriate), and functions that reflect changes in the efficiency of the technology and mix of stock over time.

Residential end-use analysis is typically combined with a sector-based approach for the non-residential and non-revenue water sectors to obtain a forecast for total demand, and the historical portion is calibrated against climate-corrected bulk water demand. This hybrid demand forecasting method is currently emerging both nationally and internationally as best practice (Turner et al. 2006, 2008c) and is detailed in Turner et al. (2010).

However, a complete picture of urban water demand includes other factors that are not directly addressed by the above analyses. Figure 3.1 depicts the complex array of factors that may need to be accounted for when generating a demand forecast. The simple LCD and sector analysis forecasting methods on their own rely on a historical average to generate forecasts and generally do not allow for the impacts of structural (for example, growth in more efficient stock such as toilets) or other changes to the urban water system (for example, increased dependency on source substitution, such as rainwater and major reuse). End-use analysis can accommodate changes in demographics and land use, changes associated with improving the efficiency of water-using appliances and, to a limited extent, changes in the way people use those appliances.

Figure 3.1: Typical factors affecting demand



Source: Turner et al. (2010).

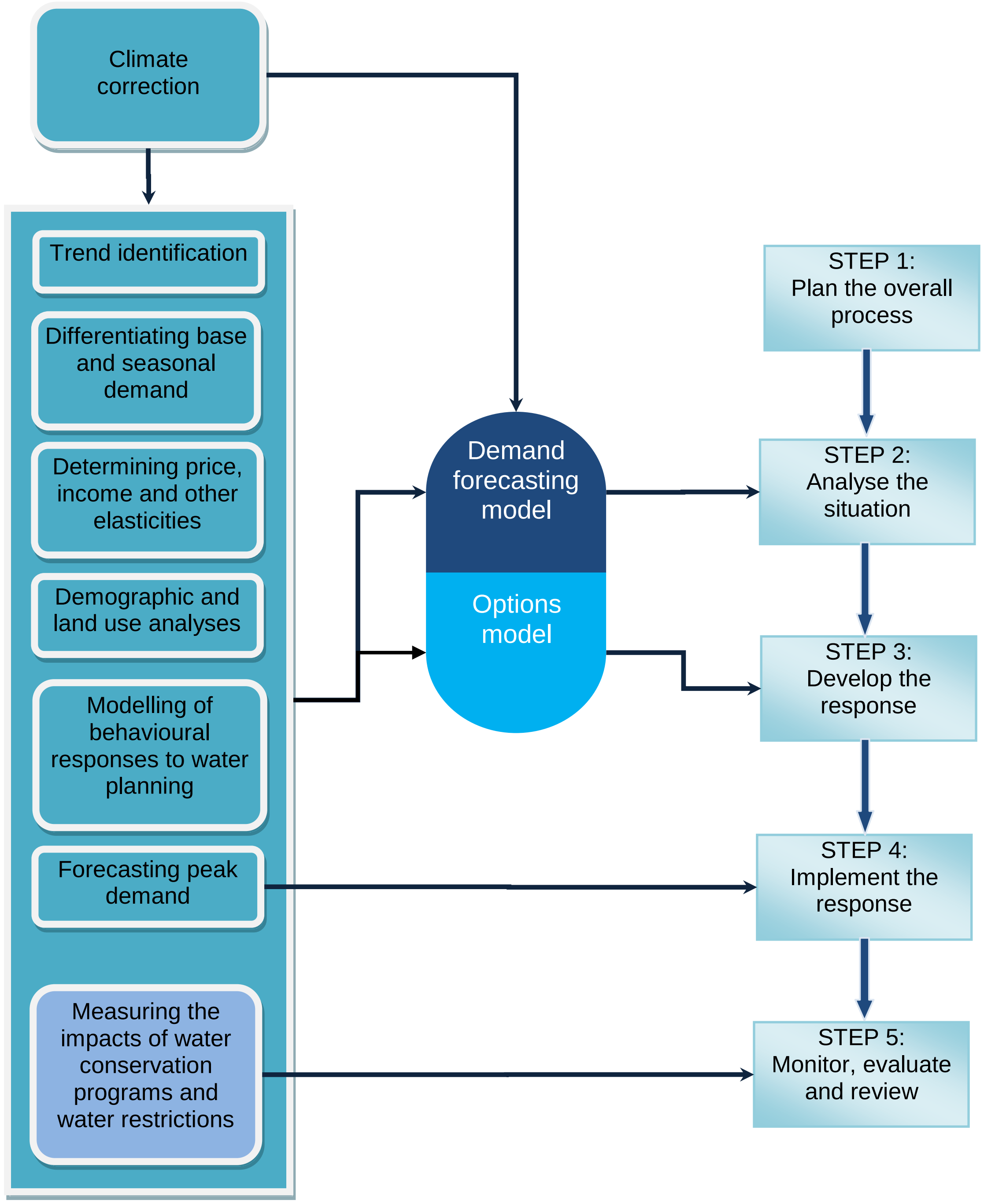
The primary forecasting methods described are of limited use when they are applied in isolation. This is due to their limited ability to adequately account for changes in demand caused by external factors such as climate, economic and sociocultural factors, and regulation. The advent of water restrictions, volumetric and inclining block tariffs and structural and behavioural demand-management initiatives complicates matters even further. Hence, it is necessary to complement these primary forecasting methods with other analytical techniques that adequately investigate and reflect the impacts of the additional factors. Typically, an empirical approach of formulating statistical models that describe historical bulk water production and customer meter demand is employed to understand the effect of external factors on demand over time. This can reveal the demand response to changes in particular conditions to provide further insight into how water is used, how its use can be forecast more accurately and, ultimately, how demand can be reduced by multiple instruments and measures in both the short and long terms.

3.1.3 Complementary techniques and the IRP framework

Analyses and forecasts of urban water demand are undertaken in a variety of contexts and for differing purposes, ranging from specifically tailored peak daily demand models for short-term supply system optimisation to studies investigating the influence of household characteristics and behaviour on demand for long-term supply–demand planning.

Figure 3.2 illustrates the various forms of analyses that can be used to complement the three primary forecasting techniques and the role of the complementary analyses in the IRP process (see Appendix 3A for a more detailed depiction of the complete IRP process). These approaches are often employed from differing perspectives or disciplines (engineering, planning, economics etc.). However, they all embody some form of historical demand analysis and share the ultimate goal of obtaining a stronger understanding of demand drivers.

Figure 3.2: Complementary demand analysis techniques and their potential roles in the IRP process



Note: Measuring the impacts of water conservation programs and water restrictions is not addressed in this paper. See Chapter 5, *Techniques for estimating water saved through demand management and restrictions* (Fyfe et al. 2010a).

The analysis results obtained from these different techniques can, to varying extents, be used to inform water supply–demand forecasting and planning in the short, medium and long term. Significant care needs to be taken, however, before adopting any of these complementary techniques, to determine the primary aim of the data collection and analysis. For example, will the outcomes of the analysis adequately inform the demand forecasting exercise or merely provide a limited snapshot of demand of an unrepresentative sample that is not statistically valid and therefore cannot be used for a broader population? Consideration of the aim of the analysis, the resources and time needed, the costs of data collection and analysis, and the eventual benefits is essential.

3.1.4 Summary of complementary techniques

Each of the analytical techniques identified in Figure 3.2, excluding 'Measuring the impacts of water conservation programs and water restrictions', is explained in detail in the following sections of this resource paper. Each section includes examples of their application from the literature (where available), an overview of their pitfalls and limitations, and potential solutions to those problems. Detailed coverage of 'Measuring the impacts of water conservation programs and water restrictions' is not provided in this paper. Step 5 in the *Guide to demand management and integrated resource planning for urban water* (Turner et al. 2010) and *Techniques for estimating water saved through demand management and restrictions* (Fyfe et al. 2010a, Chapter 5) provide specific details on the techniques used for gauging the impacts of water efficiency initiatives after implementation.

Table 3.1 summarises the techniques considered in this paper, their purpose in relation to demand forecasting, data requirements, guidance on experience needed (for example, their suitability for experienced versus inexperienced practitioners) and the stage of the planning process at which they are most useful (such as high-level strategic versus detailed planning). While categories of analyses developed for the purposes of this paper were designed to provide clarity, the reader will find that there is much overlap in purpose and approach between many of the analyses described. Hence, readers are encouraged to view the categorisation as a guide only and to select and cross-match techniques as they see fit for their purposes.

The final section of this paper examines more closely how the various techniques can be used within a broader framework to forecast water demand.

Table 3.1 Summary of analytical techniques

Technique	*Purpose*	*Reference / base case or options projection*	*Data needs*	*High-level strategic planning versus detailed planning*	*Experience level / expertise*	*Link to primary forecasting techniques and/or options model*
Climate correction	Removing the influence of weather to provide a reference case for forecasting. Revealing changes to the demand regime. Tracking demand against consumption targets.	Reference / base case	Minimum: reservoir corrected BWPD and standard BoM data (i.e. rainfall, evaporation, temperature). Advanced: BWPD + binned CMDD, BoM data	Historical demand should always be climate corrected. Basic analysis for strategic planning. In-depth analysis for detailed planning.	Advanced	Calibration of end-use models, starting point for LCD / sector-based forecasts
Trend identification	Informing further analysis and forecasting.	Reference / base case	BWPD and/or CMDD	Strategic and leading in to detailed analysis	Basic–medium	LCD and sector-based projections
Differenti-ating base and seasonal demand	Informing end-use models and peak demand-management options.	Reference / base case	BWPD and/or CMDD	Detailed	Basic–medium	End-use / sector-based hybrid forecasts. Options development.
Forecasting peak demand	System optimisation and investigation into constraints.	Reference / base case	BWPD, BoM, population	Detailed operational	Medium–advanced	Describing the peaks for LCD, sector-based and end-use forecasts.
Determining price, income and other elasticities	Under-standing the historical effect of price, income and other socio-economic factors. Developing options and associated policy.	Options	Basic: BWPD, price, BoM data Advanced: CMDD, socio-demographic data, household data.	Detailed	Advanced	Design of options. Setting end-use model parameters.
Demographic and land use analyses	Under-standing the context of demand. Investigating specific subsectors.	Reference / base case Options	CMDD, socio-demographic data, planning data, spatial data.	Detailed	Basic—advanced	Informs sector breakdowns, end-use models. Development / design of options

Technique	*Purpose*	*Reference / base case or options projection*	*Data needs*	*High-level strategic planning versus detailed planning*	*Experience level / expertise*	*Link to primary forecasting techniques and/or options model*
Modelling of behavioural responses to water planning	Investigating options scenarios.	Options	CMDD, behavioural, sociodemo-graphic, market segment-ation, end use	Detailed	Advanced	Options modelling

BoM = Bureau of Meteorology; BWPD = bulk water production data; CMDD = customer meter demand data; LCD = litres per capita per day.

3.2 Climate correction

Climate correction is used both to describe the seasonality of the water demand profile of a given area or sector and to explain weather-induced temporal variability of that profile.[1] This aids in determining the extent to which observed departures from the typical seasonal profile are driven by weather fluctuations or other factors, such as water restrictions or changes in pricing regimes. Correction for climate- and weather-driven fluctuations in demand is fundamental to understanding historical demand and to forecasting future demand (Step 2 of the IRP process, 'Analyse the situation'), as the use of uncorrected demand data can lead to misinterpretation of observed shifts and trends in demand and grossly inaccurate forecasts.

Primarily, climate correction models are used to establish an appropriate starting point for demand projections, ensuring that the starting point for a forecast is based upon a figure for demand that is representative of typical seasonal demand and not influenced by atypical weather (Beatty et al. 2007b). In an LCD- or sector-based forecast, this amounts to correcting for weather and climate to then extrapolate current demand based on population (or other base unit) growth. When employing an end-use forecasting approach, climate correction will involve identifying weather-neutral per capita demand against which the weather-sensitive components of an end-use model can be calibrated.

While climate correction is critical to developing an accurate forecast using any of the three primary forecasting techniques, it also underpins or is an important secondary step to all the complementary demand analysis techniques discussed in this paper. Trend analysis (Section 3.3) and demographic and land-use analysis (Section 3.7) should ideally be performed on climate-corrected demand, or at least interpreted with direct reference to corresponding climatic conditions. Estimation of the split between base and seasonal demand (Section 3.4) and modelling of water user behaviour (Section 3.8) should also incorporate some form of climate correction. The methods used in econometric estimation (Section 3.6) and peak demand forecasting (Section 3.5) are indeed founded upon the relationship between weather and demand.

When undertaking monitoring and evaluation (Step 5 of the IRP process), climate correction may be used to track water use against consumption targets (Maheepala and Roberts 2006). Like econometric estimation, regression approaches to the evaluation of water restrictions and conservation programs have climate correction at their core. Other evaluation techniques must either be applied to climate-corrected demand or accommodate variation associated with climate in some other way, such as by employing appropriate statistical controls.

[1] The distinction is made here between the recurring patterns of climate that drive seasonality in water demand and the fluctuations in weather that produce departures from long-term seasonal averages. While the primary purpose of climate correction is to factor out the 'noise' of weather, the term 'climate correction' is meant to encompass the dual functionality that the analysis has in terms of explaining both seasonal and stochastic (weather) variability.

Adjusting for weather and climate is addressed in more detail in *Techniques for estimating water saved through demand management and restrictions* (Fyfe et al. 2010a, Chapter 5).

An ancillary use for climate correction models is their application in assessing the impacts of climate change on urban water demand. Some examples of this are presented in Box 3.1 in Section 3.2.2.

3.2.1 Techniques

Correcting for climate and or weather typically involves generating a statistical model using ordinary least squares (OLS) regression, the output from which is then used to normalise observed demand against weather-related fluctuations. The regression model describes the empirical relationships between aggregate water demand for a particular region or sector (the dependent or response variable) and corresponding meteorological data (the independent, explanatory or predictor variables).[2] A climate correction model is effectively a statistical interpretation of the way a given population (residential or other) changes the amount of water it consumes in response to changing weather conditions. Central to this analysis, whether implicit in the regression modelling or performed as a separate preliminary procedure, is the process of generating a seasonal profile of demand. By correcting observed demand for weather-induced fluctuations, one can thus identify departures from typical seasonal water demand patterns and discern underlying trends that are driven by other factors (changing demographics, water restrictions etc.).

The formulation of a climate correction model typically involves performing a multiple regression on water demand in a selected 'baseline' period. Outside of this baseline period, there is no certainty that the derived relationships will hold. Therefore, climate correction models are not used to generate demand forecasts directly, but rather to inform other forecasting techniques (such as end-use modelling). Once a regression model has been formulated, climate-corrected demand can then be determined using one of a number of the techniques described under 'Determining climate-corrected demand' in this section. The following sections discuss the considerations that inform a climate correction analysis. The key considerations in developing an OLS regression model for climate correction and other forms of urban water demand analysis are presented in Appendix 3B.

Data types and correction approach

The type of data used in a climate correction model will depend on the purpose of the correction and availability. Most commonly, climate correction is applied to (reservoir-corrected) bulk water production data (BWPD) normalised to the population (that is, expressed as LCD), as this is the most readily available and easy to process (a single time series with frequent readings). Indeed, this is a straightforward and valid approach to tracking performance in meeting demand reduction targets. However, when seeking to generate climate-corrected demand figures against which to calibrate end-use models, a method of apportioning the climate correction between the different sectors is preferred because the influence of climate will differ among single residential, multiresidential, commercial, industrial and other non-residential sectors.

One approach is to apply the corrections derived from modelling BWPD to the aggregated customer meter demand data (CMDD) from climate-sensitive sectors. Such an approach was reportedly used in an analysis by Beatty et al. (2007b), in which the outputs from a climate correction model on BWPD were used to generate a lagged index of climate influence. The index was then applied to aggregate CMDD from individual sectors to generate climate-corrected demand for those sectors. That approach assumes a constant climate effect across sectors. A more discriminating alternative is to identify a particular year in the recent historical bulk water production records that most closely approximates climate-normalised demand (that is, the year that requires the smallest climate correction). Demand forecasts for those sectors with seasonal water-use profiles are then calibrated to the sectors' respective CMDD

[2] Other variables may be necessary when there are additional underlying factors that influence demand, such as significant changes to the pricing regime or the introduction of or changes to water restrictions.

from that year. Another alternative is to correct historical CMDD, expressed on a per active billing account basis, for each of the sectors that is climate sensitive.

The main limitation with the first alternative is that there may not be a particularly 'climate-neutral' year within the recent past to calibrate from, especially one that is not affected by other complicating factors, such as water restrictions. There is also a degree of uncertainty related to how best to identify a climate-neutral year. The second approach introduces the complexity of aggregating and generating a seasonal profile from CMDD that is made up of individual meter readings taken at less frequent (typically quarterly) and varying (between users) time intervals. To overcome this, individual customer meter records may be 'binned' (see Appendix A in Turner et al. 2010) and then aggregated into a uniform time step. The choice between the two approaches will depend on:

- the availability and quality of BWPD and CMDD
- the customer billing interval (ideally quarterly or more frequently)
- the technical capacity for developing a binning algorithm
- the complexity of the historical demand record.

Selecting a baseline calibration period

The selection of an appropriate baseline period against which to calibrate a climate correction model is critical to the proper interpretation of the outputs and their integration with other demand analyses and, ultimately, a demand forecast. The key considerations that inform the selection can sometimes be in conflict, in which case a judgment based on an understanding of the system will be necessary.

First, the calibration period should be as long as possible to maximise the variation in the response data to be modelled and thus help derive a more robust model. Weber (1989) suggests a three-year calibration period as a minimum for regression models of monthly data, while DEUS (2002) recommends at least one year for calibration of a daily time-step regression.

In selecting the time window for the baseline period, it is advisable that the calibration encompass or be as close as possible to the period to be corrected. It is also essential to recognise the potential effect of changes to the underlying demand regime that might be caused by factors such as:

- changing community attitudes and behaviour under conditions of water scarcity
- widespread adoption of new water-efficient practices and technologies
- new water restrictions
- major changes to the pricing regime.

Such factors fundamentally inform the manner in which consumers use water (particularly discretionary use) and, consequently, the manner in which they adjust their water use in response to seasonal and stochastic weather variation.

Two main methods of accommodating shifts in the demand regime when selecting a baseline period are reported in published literature. Maheepala and Roberts (2006) recommend that the baseline calibration period be the same as (or encompass) the period to be corrected to ensure that the demand regime for both the calibration and the correction are the same. *Water demand trend tracking and climate correction* (DEUS 2002) describes a method of adjusting a climate correction to allow for changes in the demand regime. Essentially, a quadratic relationship between the observed demand to be corrected and the demand predicted using a regression model (calibrated to an earlier period) is derived, the equation for which is used to quantify any shift in the demand regime.

While both techniques ensure that the climate correction adequately reflects the prevailing demand regime of the time, they do not account for changes to the demand regime that may occur over the course of the baseline calibration period. This suggests that, in selecting a baseline period, the analyst must choose a time window in which the factors that can affect the demand regime remain constant. In times of dynamic shifts in water policy, it may not always be possible to ensure that the baseline demand regime is stationary, particularly where the Maheepala and Roberts (2006) method of recalibrating the regression model to the period being corrected is adopted. To overcome this, it may be possible to utilise regression variables that account for the effect of factors that shift the demand regime (see 'Explanatory variables', below). In doing so, however, the analyst must consider how those variables are then handled in the subsequent correction process (see Section 3.2.3).

Explanatory variables

Air temperature, rainfall and evaporation are typically the focus of climate correction models because they are considered to be the measurable climatic factors that water users respond to either directly or indirectly. Temperature and rainfall are tangible factors that people might respond to directly when using water—for example, someone may decide to water their garden in hot, dry weather or not to do so when it is raining. In terms of residential demand, evaporation could be considered a less tangible variable and could be considered a proxy variable for demand from gardens, swimming pools and evaporative cooling. Evapotranspiration might be used in place of (pan) evaporation where irrigation demand is the primary driver. Appendix 3B provides a discussion on the specification of meteorological variables in regression models of water demand.

As mentioned in the previous section, a climate correction model is ideally calibrated to a baseline period over which there are no significant changes to pricing, regulation and other factors that influence underlying water usage patterns. This ensures a simple model and produces more reliable empirical relationships between demand and weather. However, if the historical record that is to be analysed unavoidably encompasses significant changes to those factors, variable specifications that adequately explain the effect of the changes must be developed. Specifications of the main non-climate variables that may be relevant in a climate correction model are discussed below.

Trends associated with behavioural and technological change

In areas where changing water-use behaviours and technology among consumers are contributing to a gradual change in average water demand, the inclusion of a trend variable in a climate correction model may be warranted. A linear or non-linear trend can be specified as a function of time (Weber 1989). To accommodate more complex non-stationary trends, Billings and Jones (2008) suggest using a centred moving average of observed demand (see Section 3.3.1) as an explanatory variable. However, that variable is not truly independent, raising questions about the validity of this specification. Readers are advised to refer to texts on time series analysis for more detailed treatment of handling trends in regression analysis.

Water restrictions

The introduction, adjustment or retraction of water restrictions can dramatically alter the seasonal demand peak and in some cases also affect base demand. The simplest variable specification that may be used to explain the effect of restrictions is a dummy variable—a binary expression of the presence or absence of a given state of restrictions. Where there are multiple changes to the restrictions regime, additional dummy variables may be required, although it is sometimes possible to lump different restrictions levels into the one variable.

A simple dummy specification, however, will only shift the intercept of a regression model; it does not accommodate the fact that the relationship between weather variables and demand may also change under changes to restrictions. Where a dummy specification is not adequately explaining the effect of a change to restrictions, it may be helpful to introduce interaction terms between the dummy variable and the weather variables being used in the model. Essentially, such interaction terms allow the model to adjust the relationship between demand and a weather variable when restrictions change. The interaction term in this case is defined as the cross-product of the mean-centered[3] weather variable of interest with the restrictions dummy variable. Analysts with limited OLS regression experience are advised to consult statistical modelling texts before attempting to use and interpret interaction terms.

[3] The variable mean is subtracted from each data point.

Water price

The effects of price changes are more complex and are often the focus of dedicated analyses as described in Section 3.6. However, it is inadvisable to use the sophisticated variable specifications and estimation techniques from price analysis in climate correction modelling. However, where a large change to the water tariff or tariff structure results in an observable change in the demand profile, the effect may be modelled using a simple dummy variable to represent the presence of the new tariff and, where the effect appears to be more pronounced on peak demand, interaction terms between weather variables that inform peak demand (temperature, evaporation) and the dummy variable.

Determining climate-corrected demand

Once a climate correction regression model for water demand is finalised, the output of the model is used to generate a 'climate-corrected' demand figure or series. There are a number of techniques available to undertake this. Common to most is the formulation of a demand 'hindcast'—a synthetic historical time series of predicted demand that essentially represents the spectrum of demand that would theoretically have been observed in the calibration period had the range of past climatic conditions occurred in that period. The hindcast is generated by applying the equation from the calibrated regression model to the longest available record of historical weather data. It is used as the basis for determining demand under 'normal' weather conditions, which in turn is the basis for correction of observed demand.

DEUS (2002) describes a climate correction method that can accommodate shifts in the underlying demand regime, thereby negating the need to recalibrate the model at critical junctures such as the introduction of water restrictions. Climate-neutral base and seasonal demand are first calculated from the demand hindcast from a regression model of demand that uses temperature, rainfall and soil moisture as predictors. Base demand is assigned to be the minimum demand in the hindcast record. Seasonal demand is calculated as the difference between a frequency-weighted average of the hindcast demand estimates and base demand. Observed demand from the period to be corrected is then plotted against predicted demand for the correction period. Any fundamental change in the relationship between weather and demand (the demand regime) over that period is signified by a divergence away from the line of direct equality (that is, the line y = x). A polynomial curve is fitted to this plot, the equation for which is used to calculate the percentage change in both fixed and seasonal demand relative to the baseline period at any given day or month. The climate-corrected demand at time *t* is then calculated as:

$$D_{MA,t} + \left(1 + \%\Delta D_t\right) \cdot \left(D_B - \hat{D}_{MA,t}\right) \qquad 1$$

where

$\%\Delta D_t$ = Percentage change in seasonal demand over the past year (relative to the baseline) at time *t*

D_B = Long-term average demand calculated from hindcast

$D_{MA,t}$ = 1-year prior moving average (see Section 3.3.1) of observed demand at time *t*

$\hat{D}_{MA,t}$ = 1-year prior moving average of predicted demand at time *t*

The term ($D_B - \hat{D}_{MA,t}$) in the above equation represents the raw climate correction. Any necessary adjustments for shifts in the underlying demand regime are defined by the change in seasonal demand as reflected in the preceding term. The need to select a calibration period that is itself unaffected by shifts in the demand regime is not stated but is presumed implicit to the process.

The method proposed by Maheepala and Roberts (2006) also makes use of a demand hindcast to define climate-neutral demand. As in the DEUS (2002) method, the hindcast is generated by feeding 30 or more years of historical weather data into a regression model fitted to daily or monthly water use. Climate-normalised demand for a given period (say, a year or month) referenced to the baseline calibration period is interpreted to be the corresponding median or 0.5 probability (yearly or monthly) demand from the hindcast record. The climate correction for the period of interest (relative to the chosen baseline period) is simply the difference between the predicted demand (using the regression model) and the climate-normalised demand. As mentioned above, shifts in the underlying demand regime are accounted for by recalibrating the model to reference the period that the climate correction is to be applied to.

The W*ater resources planning manual* (Maddaus 2007) presents a different methodology again for determining climate-corrected demand. Deseasonalised monthly demand data is used to fit a regression model with normalised explanatory weather variables. The resulting model coefficients represent the change in demand associated with departures from long-term monthly averages. Corrections to observed demand for weather-induced fluctuation are calculated as the differences between observed and long-term average weather (for example, temperature and rainfall) multiplied by the corresponding model coefficients. A 13-month centred weighted moving average can then be applied to deseasonalised, weather-corrected data to track trends and cycles that reflect changes to the demand regime.

3.2.2 Examples

In developing a demand forecast for metropolitan Adelaide, Turner et al. (2008a) recognised that a correction developed from BWPD is not necessarily applicable to individual sectors (residential, commercial etc.). Accordingly, they sought to identify a relatively climate-neutral year in the available historical customer meter record that could be used to calibrate the outdoor residential component of an end-use forecasting model. The climate correction approach devised by Maheepala and Roberts (2006) was thus adapted, a monthly regression model was calibrated and validated on four and two years of BWPD, respectively, and the median annual demand from the 30-year model hindcast was taken as climate-normalised annual demand. The year of the production record that required the smallest climate correction relative to climate-normalised demand was then selected as the calibration year for the end-use model.

Beatty et al. (2008) used a climate correction and trend tracking approach similar to that described by DEUS (2002) to explore the impacts of the introduction of volumetric pricing and water restrictions on residential and non-residential demand in Melbourne. This form of climate correction was also applied to annual demand data (per property) from utilities around Australia to investigate trends in residential demand under recent drought conditions (Beatty et al. 2006). Similar approaches have been taken to:

- track trends in production data from Rous County in northern New South Wales (Australian Water Technologies 2002)
- examine demand trends in south-east Queensland (Beatty et al. 2007b), Dubbo (Beatty et al. 2007a) and Melbourne (Beatty et al. 2008)
- gauge the change in consumption following the introduction of a demand-management program in Kalgoorlie–Boulder (Sarac and White 2001)
- measure the impacts of water restrictions in Sydney (White et al. 2000).

Table 3.2 summarises a number of climate correction studies reported in Australia.

Table 3.2: Australian examples of climate correction analyses

Author	*Location*	*Type of data*	*Baseline calibration*	*Time step*	*Correction method*
Turner et al. (2008a)	Adelaide	BWPD	4 years, no restrictions	Monthly	Selection of a climate-neutral year based on smallest correction using difference between predicted annual demand and median annual demand from hindcast
Beatty et al. (2008)	Melbourne	BWPD	1 year	Daily and monthly	Seasonal climate correction index generated from BWPD model applied to CMDD. Correction based on difference between 1-year moving average of predicted demand and hindcast average demand, adjusted for changes in the demand regime
		CMDD	4 years, no restrictions	Quarterly	
Beatty et al. (2007a)	Dubbo	CMDD	Unknown	Quarterly	Unknown
	West Melbourne	BWPD		Daily	Difference between 1-year moving average of predicted demand and hindcast average demand, adjusted for changes in the demand regime
Beatty et al. (2007b)	South-east Queensland	BWPD	6.5 years	Monthly	Lagged correction index generated from BWPD model applied to CMDD. Correction based on difference between 1-year moving average of predicted demand and hindcast average demand, adjusted for changes in the demand regime
Maheepala & Roberts (2006)	Yarra Valley Water (Melbourne)	BWPD	Year to be corrected	Daily and monthly	Difference between predicted demand and median (or 0.5 probability) demand derived from hindcast
Beatty et al. (2006)	Australian capital cities	Annual consumption data reported by WSAA	Unknown	Annual	Unknown
Australian Water Technologies (2002)	Rous County (northern NSW)	BWPD	1 year	Daily	Difference between 1-year moving average of predicted demand and hindcast average demand, adjusted for changes in the demand regime
Sarac & White (2001)	Kalgoorlie–Boulder	BWPD	1 year	Daily	Difference between predicted demand using the equation derived from the calibration year and observed demand
White et al. (2000)	Sydney	BWPD	1 year	Daily	Difference between 1-year moving average of predicted demand and hindcast average demand, adjusted for changes in the demand regime

BWPD = bulk water production data; CMDD = customer meter demand data; WSAA = Water Services Association of Australia.

Box 3.1: Modelling the effects of climate change on urban water demand

Regression models of the form used for climate correction have also been used to model the impacts of climate change on urban water demand. Maheepala (2003) used regression modelling on a monthly time step to predict changes in mean bulk annual per capita consumption under various 2030 climate change scenarios in Benalla, Victoria. The model used rainfall and evaporation as predictor variables and produced strong fits to observed data in both the calibration period and the validation period. Similarly, Moglia et al. (2009) formulated monthly regression models for particular sectors within various water supply zones of Sydney for the purpose of exploring climate change scenarios. Their modelling approach produced strong fits for single and multiresidential, government and primary producer sectors. It was less effective for predicting demand in commercial and industrial sectors, presumably due to the lack of responsiveness to climatic conditions within those sectors. The use of regression modelling to assess climate change impacts on water demand has also been reported (Beatty and O'Brien 2007). For a discussion on incorporating climate change into the IRP process, refer to Chapter 4, *Incorporating climate change into urban water IRP* (Fane et al. 2010, in this document).

3.2.3 Pitfalls, limitations and potential solutions

While the three climate correction methods described above under 'Determining climate-corrected demand' can accommodate shifts in the demand regime outside the baseline calibration period, they do not address the case of having to use a baseline period that encompasses a shift in the demand regime. While in the past this may have been a highly unusual situation, the dynamic nature of drought response in urban water planning has meant that water restrictions in many urban centres have been adjusted several times in a single year. The longer this state of affairs continues, the more distant—and therefore less viable for model calibration—unrestricted years become.

Calibrating a climate correction model to a year in which the demand regime is in flux would require a set of variables to reflect the changes that are taking place (as described under 'Determining climate-corrected demand'). This in turn introduces the problem of defining climate-neutral demand, as the analyst must choose how to set the non-climate explanatory variables when generating the hindcast. That choice will be informed by the purpose of the correction and the demand regime that the correction is intended to represent. For example, if the correction is intended to provide a climate-normalised figure to base a forecast upon, then the forecaster may have to decide whether or not future demand is to be constrained by permanent water saving rules (similar to low-level restrictions), or whether the current or the previous pricing regime will be in force. The corresponding variables in the regression model must then be set to reflect those preferences in the hindcast used to derive climate-neutral demand.

Shifts in the demand regime can be demonstrated by selecting a stationary period as a baseline reference and revealing the divergence between observed demand and predicted demand (see for example Beatty et al. 2008). In such analyses, inferences about departures from predictions should always be made with reference to prediction intervals of the simulated demand, not confidence intervals (see Box 3.2). Moreover, it is important to be aware of the limits of extrapolating regression model outputs beyond the calibration period. The reliability of a regression model theoretically extends only as far as the bounds of its calibration data domain. For example, if temperature only ever reaches 30°C in the calibration period but rises to 32°C outside the calibration, caution should be exercised when making inferences related to the prediction because the real demand response may become magnified (non-linear) above 30°C. For this reason, DEUS (2002) recommends selecting a baseline year that has the widest possible variation in weather conditions to ensure that the form of the relationships between the independent and response variables will hold when applied outside the calibration window.

Box 3.2: Model uncertainty: confidence intervals versus prediction intervals

When making inferences about shifts in the demand regime based on climate correction modelling, it is worth noting the distinction between confidence intervals for the mean and confidence intervals for the prediction (or confidence intervals and prediction intervals). It is not uncommon for 95% confidence intervals (for the mean) to be stated as the measure of uncertainty against which the significance of trends in observed data away from predictions is assessed. That measure actually overstates the strength of the predictions, as it signifies the range of values within which one can be 95% sure that the mean for all observed values corresponding to a given set of predictor data will lie. The confidence intervals for the mean are calculated according to the equation

$$\hat{y}_0 \pm t_{[\alpha/2]}^{(n-2)}\, s \sqrt{\frac{1}{n} + \frac{(x_0 - \bar{x})^2}{\sum_{i=1}^{n}(x_i + \bar{x})^2}}$$

Where

$\hat{y}_0$ = the mean value of the dependent variable when the value of the independent variable is x_0,

t = the test statistic,

n = the total sample size,

α = the probability of a type one error,

s = the standard error,

x_i = the ith independent variable,

$\bar{x}$ = the mean of the independent variables.

The 95% **prediction** interval, on the other hand, is the range within which one can be 95% sure that an **individual** observed value corresponding to a given set of predictor data will lie. The formula for confidence intervals of prediction is

$$\hat{y}_0 \pm t_{[\alpha/2]}^{(n-2)}\, s \sqrt{1 + \frac{1}{n} + \frac{(x_0 - \bar{x})^2}{\sum_{i=1}^{n}(x_i + \bar{x})^2}}$$

Prediction intervals are used to measure the uncertainty of model predictions outside the calibration period, and accordingly are always wider than confidence intervals. So when making inferences about a departure of a particular observed data point or series of points from predicted values, one should be noting the significance of the departure using the prediction interval rather than the confidence interval.

Overspecification or overfitting occurs when the number of predictor variables is high relative to the number of data points, causing the degrees of freedom of the model to be low. This is a trap that is easy to fall into, as an overspecified model can produce fits that appear to be very strong. The ramification is that the model becomes incapable of generalising beyond the fitting period; that is, it cannot be expected to produce reliable outputs when applied to data outside the calibration window. An example of this would be using dummy variables to represent every month of the year within a regression model based on a few years of monthly data. Having a justifiable rationale for the inclusion of all variables used in the model will provide a sound basis from which to avoid overspecifying a model.

Other known problems associated with climate correction modelling and potential solutions are given in Table 3.3.

Table 3.3: Other limitations of climate correction modelling and potential solutions

Limitation	*Potential solution*
High level of analysis leading to guesswork of the details	Further disaggregation wherever possible
Assumption of stationary climate	Consider using stochastically generated synthetic climate data based on different climate change scenarios (see Maheepala 2003)
Incomplete or poor-quality weather data records	Obtain a SILO[a] climate data drill for the demand- or population-weighted centroid of the area
Spatial variability of weather	Use smaller supply zones or customer meter groups for the analysis
	Obtain a SILO climate data drill for the demand- or population-weighted centroid of the area
Bias in models using BWPD caused by particular users or sectors (e.g. large industry)	Use smaller supply zones or customer meter groups for the analysis
	Subtract CMDD record of trouble users/sectors from bulk record of users/sectors causing the bias

BWPD = bulk water production data; CMDD = customer meter demand data.

a See *http://www.bom.gov.au/silo* for details.

3.3 Trend analysis

Analysis of trends in urban water demand is a simple and essential first stage in Step 2 of the IRP process ('Analyse the situation'). Trend identification can provide an indication of long-term changes in water demand on an aggregate or per capita (or household, building, employee, production) unit basis. That information can then be used to focus analysis on the factors that might be contributing to the changes. However, it is critical that analyses of trends are adjusted for weather effects (climate corrected), or at least interpreted with reference to climate and weather fluctuations, to ensure that any trends identified are not mistaken for events such as heat waves and floods or for climate variability, such as shifts in and out of drought.

Trend analysis is often performed on BWPD at a broad strategic level of planning. However, it is also valuable to look at trends within sectors and subsectors to gain an understanding of which sectors are contributing to trends at the broader level. Trend analysis by sector is also useful in developing projections of demand for LCD or sector-based forecasts. The techniques employed in this type of analysis are relatively simple and not widely reported in published materials. Accordingly, to avoid repetition, the following discussion on techniques is merged with the few reported examples of their application.

3.3.1 Techniques and examples

Moving averages

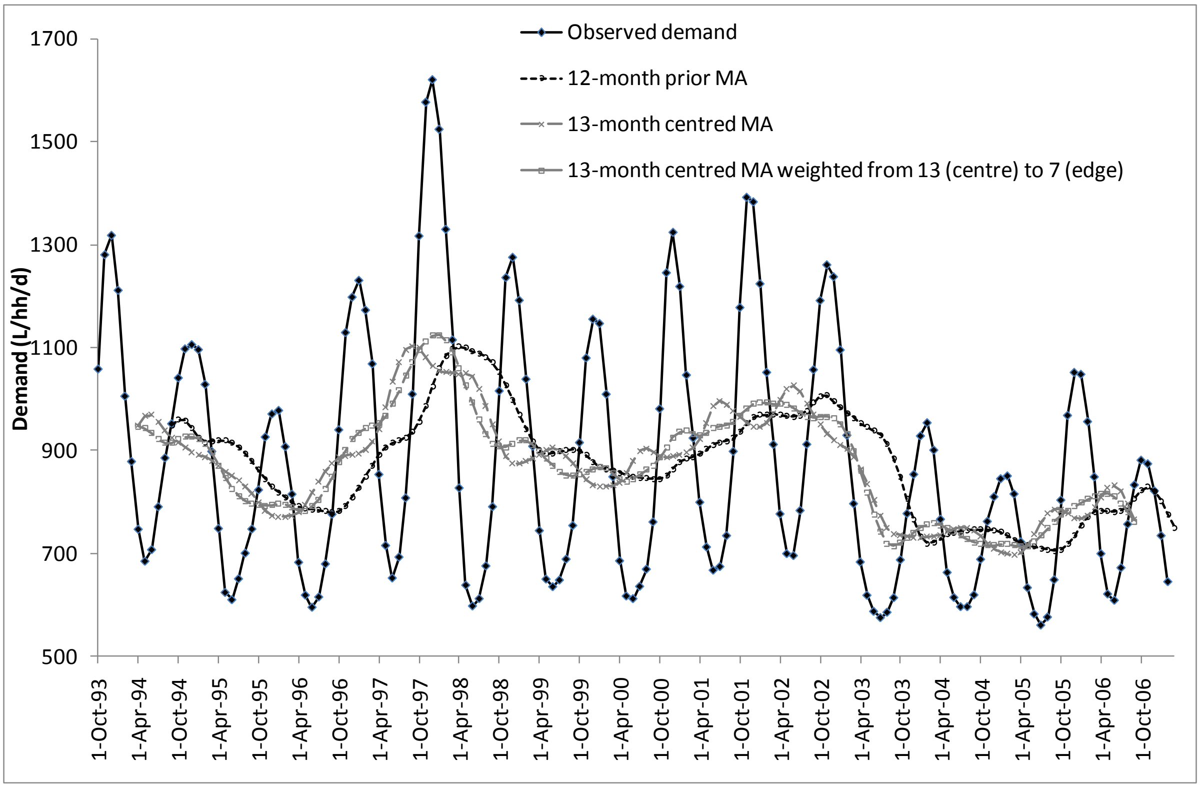
The most straightforward means of identifying longer term trends in demand is to apply a moving (or running) average to time-series CMDD or BWPD, thereby smoothing the 'noise' in the data to reveal the more general direction of demand over the period of interest (Billings and Jones 2008). Moving averages essentially de-emphasise short-term fluctuations by consolidating data points into longer units of time. There are several different types of moving average:

- *Prior moving average*—calculated from the mean of a specified number of previous data points. This is useful for viewing current demand in relation to recent historical demand (for example, monthly demand averaged over the past year using demand in the current month and the 11 months prior).

- *Centred moving average*—both past and future data are used to calculate the moving average so as to improve the timeliness in detecting a trend signal. For example, a 13-term centred moving average for a given month takes the mean of the previous 6 months' data, the figure for the month of interest and the following six months' data, thereby ensuring that there is no lag in picking up new trends in demand.
- *Weighted moving average*—also helps to address the delay of a trend signal by placing a greater emphasis on more recent data points. Weights can be applied to prior or centred moving averages. The relative magnitudes of the weightings are selected at the discretion of the analyst and may be defined by a linear or non-linear function.

Figure 3.3 demonstrates the different smoothing effects and timings of trend signal detection associated with the different forms of moving averages to historical data described above.

Figure 3.3: Different forms of moving averages and smoothing applied to time-series demand data



Seasonality and weather effects tend to be the primary forms of noise that need to be removed from urban water demand data. Smoothing using moving averages is a means of reducing that noise to allow examination of underlying average monthly, seasonal or annual fluctuations. In this sense, using an appropriate size for a moving average window—the number of data points used to calculate each average—is critical to the analysis. For example, a moving average using 365 or 12 data points can be applied to daily or monthly demand data, respectively, to smooth out seasonality and look at trends occurring over several years. Similarly, a moving average window equivalent to a month or a quarter (season) applied to daily data (say, 30 or 90 days) can remove the noise of weather fluctuation to provide a clearer indication of the seasonal nature of demand over a period of a year or longer (see, for example, Skene et al. 2009).

Moving averages are a fundamental component of the climate correction and trend tracking model described in DEUS (2002). In this approach, the climate correction at each time step is calculated from the change in seasonal demand over the (immediate) year past, relative to a climate-neutral seasonal demand (derived from a hindcast of demand as described under 'Determining climate-corrected demand'). This correction is then applied to the year-equivalent (for example, 365 days for a daily time step) prior moving average of observed demand. The output of this process is a smoothed time series of demand that shows shifts and trends that are not related to weather or climate variability.

Peaking factor analysis

Another useful technique for the identification of trends is to look at the change in peak demand and peak-to-average demand ratios over time (Billings and Jones 2008). The peak-to-average ratio (otherwise referred to as the 'peaking factor') for a given period is calculated by dividing the peak daily demand by the average daily demand for the period. Examination of the dynamics of this ratio can provide insight into changes in the seasonality of demand and the impacts of demand-management programs targeting peak water demand reduction (such as discretionary outdoor usage). Changes in the peak-to-average ratio also have significant implications for the design of water infrastructure and the potential to defer related capital expenditure.

As part of drought response planning for Sydney, Sarac and White (2001) analysed BWPD for changes over a 10-year period in average peak day, ultimate peak day and peak week demands and associated peaking factors. By using figures calculated from hindcasts of climate correction models for the years of interest, the analysis effectively accounted for the influence of weather on peak demand. The WaterTrac model described by Beatty et al. (2008) also uses climate-corrected BWPD to calculate current peaking factors. Skene et al. (2009) performed an analysis of peaking factors to reveal the effect of water restrictions on peak demand on the Gold Coast in Queensland. The analysis considered inter-annual variation of mean day maximum month (MDMM) and maximum day (MD) peaking factors between 2001 and 2008; however, the data used to generate the peaking factors was not climate corrected.

3.3.2 Pitfalls and limitations

While the above analyses can provide some insight into the presence of trends in water demand, they cannot provide explanations for why the trends are occurring. Trends in water demand can be related to a variety of factors, such as:

- natural attrition of inefficient stock—transition from inefficient to efficient fixtures and fittings over time
- changing customer attitudes and behaviour
- demand-management programs with educational and/or structural components
- water restrictions
- price changes
- adoption of new technologies that may be more or less efficient
- urban consolidation and gradual shifts to smaller lot sizes
- reducing occupancy ratios
- rezoning from non-residential to residential land uses
- growth in source substitution (such as water reuse schemes and lot-scale rainwater tanks).

Moving averages cannot unpack the root causes, but they can help to identify which to investigate further using the analytical techniques described in the following sections. As such, they are most useful in the preliminary stages of Step 2 of the IRP process ('Analyse the situation').

3.4 Analysing base and seasonal demand

A simple form of demand analysis that can be useful to aid demand forecasting is to estimate the split between base demand and seasonal demand. In the residential sector, base demand is the component of demand that is considered to be fairly constant year round (toilet flushing, clothes washer use etc.), while seasonal demand is typically associated with discretionary water usage, such as outdoor watering and the use of evaporative coolers.[4] Thus, in Australia seasonal demand is generally observed in the summer months and winter demand is largely associated with base demand.

While metering by property facilitates sector-based analysis, information on specific end-uses is virtually impossible to gather without the aid of detailed smart metering technology. Thus, from an end-use perspective the most that can be extracted from standard CMDD, read typically on a quarterly basis, is an approximate apportionment between base demand and seasonal demand and in some cases, by extension, a split between discretionary and non-discretionary demand and indoor and outdoor demand. Such estimates can be used to inform and calibrate end-use models, which use a ‘bottom-up’ approach to developing an average demand profile. The split between base and seasonal demand is also useful in helping to develop options for demand management.

The techniques employed in this type of analysis are relatively simple and often specific to the region and available data. Accordingly, to avoid repetition the following discussion on techniques is merged with descriptions of their reported application.

3.4.1 Techniques and examples

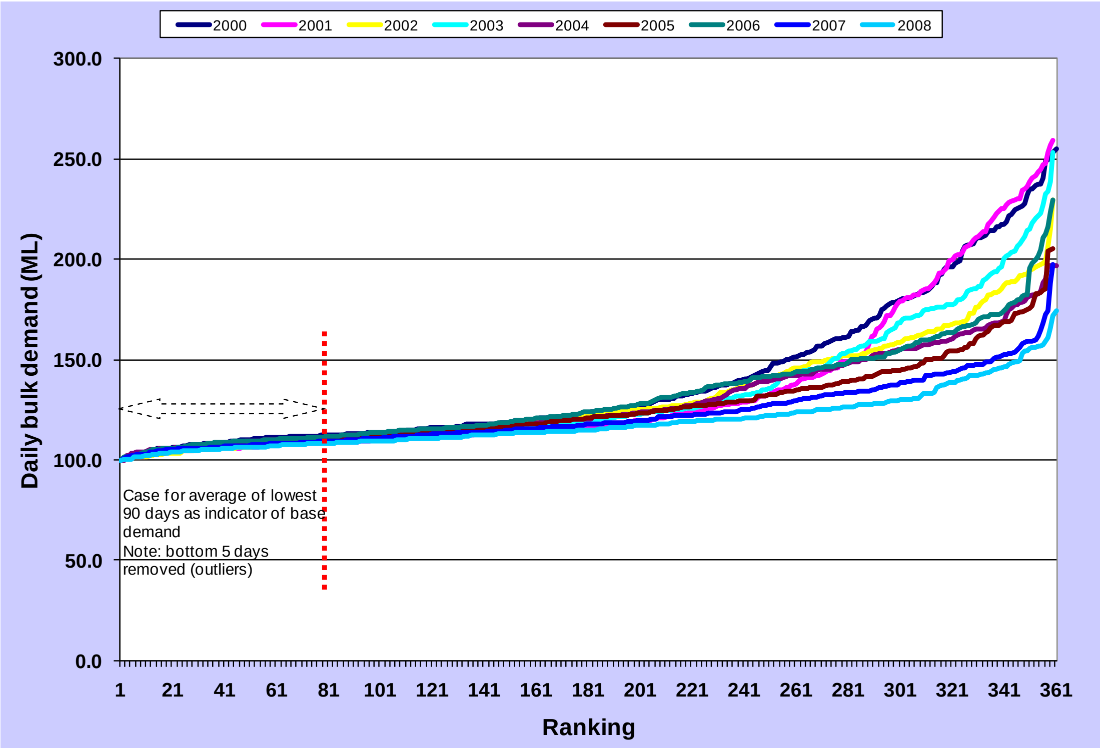
A simple approach to making the distinction between base demand and seasonal demand is to subtract average low period (winter) demand from peak period (summer) demand (Billings and Jones 2008, Danielson 1979). In their model of daily demand in Melbourne, Zhou et al. (2000) estimated base demand by fitting a polynomial to the time series of BWPD (normalised to population and averaged by month) in the lowest months of water consumption through the year. DEUS (2002) and White et al. (2000) both determined fixed (base) demand using the hindcast from a climate correction model fitted to LCD BWPD. After fitting a regression model to a particular ‘baseline’ period, indoor demand was taken to be the lowest daily production in a demand hindcast (historical time series prediction) based on historical climate data.

Water resources planning (Maddaus 2007) suggests using the month of the year with the lowest seasonal demand index (refer to Appendix 3B) as the indicator for base water demand. Base demand is then calculated on monthly BWPD or CMDD by multiplying the weighted moving average for each month by the selected base month index. Seasonal demand is estimated using the difference between the calculated base demand and observed total demand.

An alternative approach works on the principle of making the distinction between non-watering days where there is limited demand variability and days of high variability associated with watering and other seasonal uses (Roberts 2009). Daily BWPD is ranked and indexed to generate a plot that provides a graphical indication of the variability of demand over a year. Base demand is interpreted as the average of the lowest 90 days, as illustrated in Figure 3.4. Daily demand figures from different years can be overlaid on the plot to indicate the reproducibility of the result.

[4] Evaporative coolers are physically an ‘indoor’ end use. However, unlike other main indoor end uses their water use and bleed-off does not go to sewer. Hence in many publications they are categorised in a similar way to outdoor watering to clarify the component of indoor water demand going to sewer from a household.

Figure 3.4: Estimation of base demand using ranked and indexed daily consumption



Source: Roberts (2009).

Gato et al. (2007a) considered the month of the year with the lowest total water use to be representative of base demand in East Doncaster, Victoria. Using daily BWPD from lowest-use months between 1991 and 1999 as the dependent variable, they produced a regression model to describe base demand with explanatory variables including maximum daily temperature, rainfall, a weekend dummy variable and an underlying trend variable. It was concluded that base use was weather-dependent because of winter irrigation.

In a separate paper, Gato et al. (2007b) determined threshold values for rainfall and temperature above or below which observed water demand was unaffected by fitting quadratic curves to plots of demand against the two variables and finding their respective maxima or minima. They then applied those thresholds to 'heat' and 'effective rainfall' functions in a regression model of base demand, again using daily BWPD from the month of lowest water use for each year as the response variable. This generated an expression for weather-independent base water use that was subsequently contrasted with the weather-sensitive regression equation for base demand described in the first paper (Gato et al. 2007a).

3.4.2 Pitfalls, limitations and potential solutions

It is important to recognise that, while some texts such as *Water resources planning* (Maddaus 2007) use base residential water use as a proxy for indoor demand, making such a link may not always be appropriate. Base residential demand as identified using the techniques described above does not necessarily directly correspond to indoor residential demand because, as Gato et al. (2007b) recognise, garden watering may be occurring even during periods of minimum demand. And despite peak seasonal use generally being associated with discretionary uses, such as watering and evaporative cooling, the assumption that residential base use directly reflects non-discretionary use is also confounded by winter watering. Similarly, the (indoor) evaporative cooling component of seasonal demand (where such appliances are prevalent) prevents us from simply using the difference between peak seasonal and base use as a proxy for outdoor demand. Thus, close attention must be paid to the distinction between base, non-discretionary and indoor demand and between seasonal, non-discretionary and outdoor demand when interpreting the seasonality of water use in a specific region.

There are a number of ways to further isolate the indoor and non-discretionary components of demand, including:

- analysis of sewer flows when/where infiltration/exfiltration are not significant
- smart metering of residential dwellings
- submetering of multiresidential blocks
- considering only minimum daily (winter) demand figures that coincide with significant rainfall
- analysis of night flows in small metered zones to detect the occurrence of night-time irrigation.

3.5 Forecasting peak demand

Analysing seasonal peak demand and forecasting short-term peak demand are common tasks in water planning and management. Understanding peak demand is essential for determining constraints in the system, understanding what can be done to relieve constraints and optimising the system in both the short and long terms. Analysis of near-term demand (measured days or hours) is typically used for supply system optimisation, maintenance scheduling and the identification and quantification of peak demand. It may be applied in the planning and design of water treatment and distribution infrastructure or, by forecasting, inform day-to-day operations. Analysis of seasonal peaks in demand may be used to inform medium to longer term planning and management of the supply–demand balance. Cutting peak demand through water efficiency initiatives can defer infrastructure investment, providing significant avoided capital and operating costs.

Near-term peaks in water demand are generally closely aligned with local weather fluctuations. In Australia, the combined effects of high temperatures, evaporation and lack of rainfall tend to generate the largest daily loads on water supplies. Seasonal peaks in water demand are similarly closely aligned with local climate, generally occurring in the height of summer in Australia.

Peak demand in the residential sector is typically associated with outdoor activities such as garden irrigation and pool and spa use, and with cooling using evaporative coolers in specific locations. In the non-residential sector, irrigation is a large contributor to peak and seasonal demand, as is water use associated with cooling towers. Demand seasonality is also evident among industries in which activity is cyclical, such as food processing and commercial tourism.

Section 3.4 explored ways of separating the base and seasonal components of demand, including analysis of peaking factors. This section deals more specifically with understanding the seasonal demand profile and near-term forecasting.

3.5.1 Techniques

A simple means of analysing daily peak demand is to generate a statistical description of the historical record of peak-to-average day demand ratios, including average, range, percentile ranks, distribution, frequencies and trends. This approach can provide an indication of the variability of daily demand, but does not link it to any driving factors and provides very limited forecasting ability.

Empirical modelling approaches are the preferred means of predicting near-term demand. Typically, a forecast model of daily (or even diurnal or hourly) demand uses recent historical demand and/or weather and other short-term forecasts as a predictive basis. A range of approaches have been employed in near-term forecasting, including various permutations and combinations of OLS regression, univariate time series, state space and artificial neural network (ANN) modelling. (Billings and Agthe 1998, Billings and Jones 2008, Bougadis et al. 2005, Maddaus 2007). These models tend to be fitted to BWPD, as this is the only form of data recorded at a sufficiently high resolution. Because they are customised to specific water supply networks, each model has its own unique structure, predictor variables and variable specifications and transformations.

Seasonal fluctuation in water demand is typically forecast in larger sub-annual time steps (typically monthly). Approaches to analysis of seasonality include seasonal decomposition and regression modelling. Multiple regression modelling is generally the preferred approach in developing a forecast that reflects demand seasonality—indeed, seasonal demand models are functionally identical to climate correction and econometric models. Although regression models alone have in the past been used to generate demand forecasts for an entire service area, they are now seen more as a complementary technique to end-use and sector-based forecasts, and are used to predict the pattern of seasonal variation rather than outright gross demand. However, where data is not available for informing an end-use model for a particular season- or weather-sensitive sector (usually non-residential sectors such as primary production and public open space irrigation), a regression modelling approach may be preferable to a simple trend-based or demand per projected base unit forecast.

The more common techniques employed in near-term and seasonal peak modelling are briefly discussed below.

Seasonal decomposition

Average monthly demand indexes (see Appendix 3B) can be applied to long-term annual forecasts to estimate the seasonal peaks in those years. However, this technique can be confounded by the influence of extreme climate in the historical record used to generate the index (particularly when less than 10 years of historical record is used to generate the index), demographic shifts, and changes to pricing, water restrictions and other factors.

Univariate time series models

The premise of time series analysis is to develop a model of demand informed solely by historical demand. A common type of univariate model is the autoregressive moving average (ARMA) model, which is made up of two main parts: an autoregressive component and a moving average component. When the demand data is non-stationary (the mean and variance change over time), an autoregressive integrated moving average (ARIMA) model is generally applied. These two types of models may be developed using the Box–Jenkins methodology. In the first step of that methodology, the data is analysed for stationarity and seasonality to determine the need for either autoregressive or moving average components in the model. Model parameters are then estimated, using least squares or maximum likelihood estimation. As a final step, model residuals are often tested for independence to ensure that the assumption of stationarity is not violated. These models are most appropriate to near-term forecasts of peak demand at an hourly or daily time step.

Regression models

As mentioned above, near-term demand models developed for particular water supply networks tend to have diverse, unique and sometimes complex specifications that are not generally transferrable to other situations. However, the principles that guide the modelling exercise are generally the same as those described in the sections on climate correction (Section 3.2) and determining price and income elasticities (Section 3.6) and in Appendix 3B.

Short-term forecasting regression models tend to explain demand variability using weather, seasonal adjustment and prior demand (lag) variables. Often these variables are subject to transformations, the functions for which are derived specifically to reflect the local conditions.

Regression models designed to examine seasonal peaks are essentially the same as climate correction models in both intent and purpose. Because daily and seasonal peak models are calibrated to, and operate on, a relatively short timeframe, other factors that may influence demand (such as water restrictions) are effectively considered to be constant. In this sense, it is wise to regularly recalibrate these models using the latest data available.

Artificial neural network models

Artificial neural networks (ANNs) are a class of models inspired by the functioning of the brain. Based upon massive parallel processing, they are capable of modelling complex, non-linear relationships without prior specification of the functional form. This has led to their use in many water resources applications, including near-term water demand forecasting. Readily attainable climatic variables typically used in regression models are also used to construct ANN models capable of forecasting peak demand. ANN models have been used to formulate daily peak demand models, but there are no known examples of ANNs being applied to longer time steps in urban water demand.

3.5.2 Examples

Near-term peak forecasting

Three separate articles by Zhou and various colleagues (Zhou et al. 2000, 2001, 2002) present short-term forecasting models for predicting daily bulk water demand (based on BWPD) in Melbourne. In the 2001 study, base consumption was initially removed from the dataset using a third-order polynomial function calibrated on the winter months. The remaining climate-dependent consumption was then modelled during the summer months with a regression model using temperature and precipitation as explanatory variables. In the 2001 study, base water use was once again removed using a polynomial function, and three separate components were then combined to predict seasonal water use: the seasonal cycle, the climatic component, and the persistence component. The seasonal cycle was modelled using a Fourier series, while the climatic component was modelled using a linear regression based upon transformations of climatic variables including temperature, evaporation and rainfall. Finally, the persistence component used an autoregressive procedure on the time series of residuals to account for short-term memory within the system. The last study by Zhou et al. (2002) extended the work from the previous study to forecast hourly water demand using daily demand.

Using daily production data, Gato et al. (2007b) adapted a regression model for predicting base use water demand developed by Miaou (1990), by incorporating threshold effects associated with both rainfall and temperature. They then separated seasonal demand into three components as in the Zhou et al. (2002) study and constructed a linear regression predicting the seasonal component using the heat function (a linear regression predicting the climatic component using temperature), rainfall, a variable indicating the day of the week, and an autoregressive technique predicting the persistence component. Gato et al. (2007a) also separated water demand into base and seasonal components. However, they applied a linear regression to predict base demand using rainfall, temperature, a dummy variable indicating the day of the week (that is, weekday or weekend) and a time variable.

Feedforward backpropagation (FFBP) ANN models have been applied to forecast short-term water demand in studies by Bougadis et al. (2005), Jain et. al (2000) and Zhang et al. (2006). The three studies typically predicted weekly water demand (production data) using a combination of significant climatic variables such as temperature and rainfall, combined with prior water demand. The ANN models were subsequently compared to simple linear regression models constructed using comparable independent variables, autoregressive time series models and/or persistence models. In general, it was found that the ANN models consistently outperformed the other models. However, only the study by Zhang et al. (2006) measured the predictive performance of the final ANN model on an independent validation set. Ghiassi et al. (2008) used a newly developed dynamic artificial neural network (DAN2) model to forecast short-term water demand for the city of San Jose, California. Hourly and daily demand were primarily forecast using past water demand data, but a temperature variable was also trialled in the hourly models with limited success. Overall, the DAN2 models were found to be superior to traditional FFBP, ANN and ARIMA models.

Coombes et al. (2000) took an unusual approach to developing a model to simulate daily outdoor water use that attempted to reflect behavioural responses to weather conditions. Rather than adopt an empirical modelling approach, they developed a model based on a set of conditional probability functions. The functions described household reaction to the occurrence and depth of rainfall in terms of outdoor water use on the day of the rainfall event and on subsequent days. Water use was in turn described as a function of daily maximum temperature or rainfall, and monthly average daily outdoor usage. The model was fitted to monthly aggregate consumption data from nine discrete supply zones in the lower Hunter region of New South Wales and was shown to effectively reproduce the strong seasonality evident in the data.

Table 3.4 summarises the key features of the near-term demand forecasting studies described above.

Table 3.4: Examples of near-term demand forecasting models

Author	*Location*	*Type of data*	*Method*
Gato et al. (2007a)	East Doncaster, Melbourne	Daily production	Linear regression
Gato et al. (2007b)	East Doncaster, Melbourne	Daily production	Regression, autoregressive procedure
Zhou et al. (2002)	Melbourne	Hourly production	Linear regression, autoregressive procedure, polynomial function, Fourier series
Zhou et al. (2001)	Melbourne	Daily production	Regression model, polynomial function
Zhou et al. (2000)	Melbourne	Daily production	Linear regression, autoregressive procedure, polynomial function, Fourier series
Ghiassi et al. (2008)	San Jose, California	Hourly and daily production	ANN (DAN2)
Zhang et al. (2006)	Louisville, Kentucky	Weekly production	FFBP ANN
Bougadis et al. (2005)	Ottawa, Ontario, Canada	Weekly production	FFBP ANN
Jain et al. (2000)	Kanpur, India	Weekly production	FFBP ANN
Coombes et al. (2000)	Lower Hunter region, NSW	Daily production	Probabilistic model

ANN = artificial neural network; DAN2 = dynamic artificial neural network; FFBP = feedforward backpropagation.

Seasonal peak forecasting

Regression modelling by sector is the fundamental forecasting approach of the Institute for Water Resources—Municipal and Industrial Needs (IWR–MAIN) Water Demand Analysis Suite. The IWR–MAIN software uses multiplicative or additive (user-selected) regression models to generate demand forecasts for six residential subsectors that are based on a standardised set of weather, dwelling characteristic and demographic explanatory variables (similar to time series econometric estimation—see Section 3.6). Coefficients used in the models can either be derived by the user or taken from a selection of default values derived from meta-analyses of previous studies that generated empirical estimates for demand equations (Baumann et al. 1997). These residential models are specifically designed to generate a seasonalised demand profile for the sector that is then extrapolated over time.

Ghiassi, Zimbra and Saidane (2008) developed ANN models to predict water demand two years and six months ahead of time to achieve cost savings through operational optimisation of a water distribution network and for capacity and financial planning purposes. The models were found to exhibit strong predictive power; however, because they exclusively used previous water demand data as inputs, they were highly site-specific and potentially insensitive to changes occurring in the system.

3.5.3 Pitfalls, limitations and potential solutions

Despite their perceived advantages, ANNs are subject to a number of specific limitations. Foremost, they are significantly more time intensive to apply compared to more basic techniques such as regression models, requiring trial and error optimisation of important network parameters and topology. Second, the risk of 'overfitting' is generally greater than for regression modelling, due to the increased number of calibration coefficients, otherwise known as 'network weights'. The risk of overfitting may be minimised through the application of more rigorous stopping criteria, which determine when exactly to cease network training. For example, an independent test set may be used to determine when to cease network training, with the optimum number of iterations defined as the number corresponding with the minimum test set error. However, the use of a test set in this manner means that it is no longer completely independent of model training, so another 'validation' should be set aside to determine the true predictive performance of the final model.

Table 3.5 lists the potential pitfalls and limitations associated with short-term demand models, along with potential solutions to the problems.

Table 3.5: Pitfalls, limitations and potential solutions associated with short-term demand models

Pitfalls and limitations	*Potential solutions*
Models are typically only valid in the short term, due to changing domains linked to changing demographics, water restrictions etc.	Continual recalibration of models on recent data
Difficultly in capturing stochastic variability	Highly optimised model specification
Models using lead variables are subject to limitations associated with climatic forecasts and their interpretation	More thorough understanding of the manner in which climatic variables influence demand
Regression models are constrained to the assumed functional form anticipated by the modeller	Intricate knowledge of the service area, or thorough optimisation of model

3.6 Determining price, income and other elasticities

These forms of analysis, broadly classed as the field of econometric estimation, attempt to quantify the relationships between water demand and characteristics that describe particular water-using strata (water utility service areas, land-use sectors, individuals or geographically defined areas such as suburbs) and the conditions that inform the water use behaviour of those strata. Typically, econometric estimation of urban water demand utilises OLS regression to formulate a model of demand in a similar fashion to climate correction. Common to most econometric models are various permutations of variables representing weather or climate (typically some form of temperature, rainfall and/or evaporation) data that are included to 'factor out' their effect on demand.

The key variable of interest in econometric models, however, tends to be price, because analysts seek to determine a demand response to changes in price (price elasticity) so as to inform pricing policy. Other variables that tend to be the subject of elasticity analyses are typically demographic variables such as income, occupancy and household composition, or dwelling characteristics such as lot size, dwelling age and type, garden size, number of bathrooms, water-using appliance stock, pool ownership and so on. These variables apply to the residential sector—indeed, that sector has been the focus of the large majority of econometric studies. Where non-residential demand is to be considered, variables reflecting land use, specific types of industries served and employment levels might be investigated.

The main characteristics and considerations of econometric estimation are summarised below. Comprehensive reviews of the techniques and applications of econometric analysis of water demand are presented in Arbués et al. (2003) and Worthington and Hoffman (2008).

3.6.1 Techniques

The principles of econometric estimation are generally the same as those underlying regression modelling for climate correction and seasonal demand forecasting. However, the critical difference between econometric estimation models and other regression models is in the forms of data used to generate the models. Aggregate water demand time-series data (BWPD or CMDD) has been used in econometric studies in the same manner as climate correction. However, the majority of studies have used cross-sectional or pooled time-series cross-sectional data. The differences between these forms of data and the associated modelling techniques are described below under ‘Data types’.

Also discussed in this section is the specification of the principal econometric variables—price and income. A number of complexities in the use of those variables cause econometric modelling to be generally more involved than climate correction. Specification of these variables, along with other variables commonly used in econometric estimation, is addressed below under ‘Variable specification’. The complexities of specifying the price variable in particular also have ramifications for the modelling technique that is employed, such that basic OLS regression is in some cases not capable of producing a reliable estimate of price elasticity. Alternative estimation techniques are briefly touched upon under ‘Estimation techniques’.

Data types

Three forms of data may be used in econometric models of water demand. The first is time-series data that is representative of the area or group under analysis as a discrete whole. Time series of explanatory variables are regressed against the corresponding time series of aggregate demand for a particular group or stratum, usually expressed as average volumetric consumption per connection or person per unit of time. The climate correction models discussed in Section 3.2 are forms of time-series regression models.

Time-series analysis is best applied to smaller segments of a utility’s service area, in which household characteristics that influence demand such as lot size or income are relatively homogeneous. When considering larger, demographically and economically heterogeneous areas, cross-sectional data that differentiates households or other classifications of service area strata may need to be analysed. A simple cross-sectional analysis slices through a point in time and considers demographic and household/strata variables that give rise to variations in the dependent variable across different households or strata.

For example, the demand of discrete local council areas (geographical strata) may be modelled using demographic and other descriptors such as average lot size, income, age etc. (Beatty et al. 2007a, Beatty and O’Brien 2008, Gaudin 2006). Alternatively, individual household characteristics determined through a survey may be used to model demand on a household-by-household basis (IPART 2004a, Turner et al. 2008a, Turner et al. 2009), although this requires high-resolution data from household surveys, which is generally not readily available. This form of analysis can be a powerful tool for understanding specific end-uses and assisting in targeting demand-management programs, as it can be used to extract the relative influence of specific end-uses such as pool ownership.

Models using a combination of the above two types of data—termed ‘panel’ data—are referred to as pooled time-series cross-sectional analyses. Here, time-series demand data for individual or discrete groups of users is regressed against continuous variables that explain longitudinal variability as well as cross-sectional variables that characterise the individual users or groups. In detecting the influence of particular variables, pooled time-series cross-sectional analyses are the most powerful because of the large sample size and the associated variance of the response variable. The large sample allows the use of numerous explanatory variables without compromising the degrees of freedom of the model and provides a larger response variance against which to fit explanatory data, which theoretically produces a more stable model estimate. There is a plethora of published materials describing various applications of this type of analysis. Some examples are Hanke and de Maré (1982), Hoffmann et al. (2006), Pint (1999), Schneider and Whitlatch (1991) and Worthington et al. (2006).

Variable specification

The manner in which variables of interest within an econometric estimation are specified can have a bearing on the result obtained from the analysis. This section discusses specification of the more commonly used variables in urban water econometrics. Specification of weather variables is addressed in Section 3.2.1, under 'Explanatory variables'.

Price

Water demand is universally regarded to be inversely proportional to water price. The effect of price on water demand, however, is most likely to be measurable when there is significant variability in the price data. If an aggregate time-series dataset is the subject of the analysis, the price variable may only be significant if there is a pricing policy shift within the modelling period that results in a notable change to the rate schedule or a restructuring of the tariff. Gradual changes in line with the local consumer price index are not likely to have a statistically significant influence on water demand (Weber 1993). Cross-sectional and panel data analyses can benefit from variability across strata in rates and/or tariff structure—for example, in studies covering an area with multiple water retailers, such as Taylor et al. (2004)—although when block tariffs are in place sufficient variability in price is likely to come from strata movements between blocks over time and any incremental price rises.

However, block tariffs on volumetric use complicate price effect estimation in two ways. First, the price paid for water under a block tariff is determined by consumption and is therefore no longer independent of the response variable. This problem of simultaneity is addressed by using alternative estimation techniques (see 'Estimation techniques', below). Second, changes in intramarginal rates are considered to introduce an 'income effect' (Arbués et al. 2003), whereby changes to a block rate above that corresponding to current consumption will potentially inform a consumer's choice as to whether or not to allow their consumption to enter the next block. A *marginal* specification of price (the unit price a user would pay for an additional unit of water in the applicable rate block) can only indicate the demand response to rate changes within the block corresponding to the current level of consumption.

The intramarginal rate income effect may be addressed by using an *average* price specification, defined as the total bill for the given period (including fixed and volumetric charges) divided by the volume consumed. An alternative (*Nordin*) specification uses a marginal price variable along with a second variable that expresses the income effect as the difference between the total bill and what the users would have paid if all units were charged at the marginal price. Various other specifications of price have also been explored, such as the price perception model and different combinations of the above specifications (Worthington and Hoffman 2006). Weber (1993) suggests that (at least) both average and marginal price should be evaluated in any price elasticity study. Indeed, where price is the critical focus of the study it may be necessary to explore a range of specifications.

Water charging structures in Australia differ between urban and rural water sectors (NWI Steering Group on Water Charges 2007). Urban jurisdictions use different combinations of fixed and variable charges within a two-part tariff structure. The variable (volumetric) component is charged by most jurisdictions according to an inclining block tariff (of between two and eight steps) that is set generally according to the long-run marginal cost of supply. The fixed charge is often determined as the residual component to be recovered after the revenue from water usage charges has been estimated. In the rural sector, charges generally comprise one or more of a wholesale water charge (where applicable), an infrastructure access fee, a usage charge and an account fee. In both the urban and rural cases, accounting for intramarginal price changes is likely to be an important consideration.

Average or marginal price may be adjusted for inflation using the consumer price index (or similar) so that it reflects the real price in the analysis. The significance of the price variable for an inflation-adjusted model can be compared with that from a model using nominal price to assess which form of price change consumers actually respond to (see, for example, Agthe and Billings 1980). Dummy variables are sometimes introduced as part of a price specification, for example to indicate when the marginal price of water is zero—that is, consumption falls within a flat fee threshold (for example, Dandy et al. 1997, Gibbs 1978). Structural tariff changes (over time or between cross-sections) may also be indicated by dummy variables and interaction terms (dummy multiplied by the price variable) where necessary.

A host of other considerations related to price specification may be relevant to an econometric model, including:

- aggregation of demand data compromising the specification of price
- the use of a lagged price variable to reflect the fact that many consumers would not keep up to date with the latest price schedules (Arbués et al. 2003)
- the fact that price may be more influential on outdoor demand than indoor demand, requiring separate models for each or some form of seasonal interaction term (Danielson 1979)
- a similar dichotomy between discretionary and non-discretionary use, causing price responsiveness to be lower in low-income houses (Worthington and Hoffman 2006).

Household income

Historically, water demand has been thought to be positively correlated with income, particularly as higher income households are more likely to have luxury end-uses such as pools and spas. Indeed, Beatty et al. (2006) found income to be a strong influence on demand (positive elasticity) in a cross-sectional analysis of the suburbs of Brisbane. However, with increased public awareness of water resource scarcity and the value of water efficiency, it is also thought that income may now be increasingly correlated with the purchase of water-efficient appliances, fixtures and irrigation systems and thus negatively correlated with demand (Turner et al. 2009). Whatever the case, income elasticity is best measured with more disaggregated cross-sectional or panel data that encompasses a wide range of income levels, as its effect on aggregate demand is likely to be difficult to separate from other factors.

Income data for geographical strata of interest can be obtained from Australian Bureau of Statistics (ABS) figures. On a household level, household value has been used as a proxy for income (Danielson 1979, Dandy et al. 1997) where actual data was not available.

Other variables

Household characteristics such as occupancy, composition, lot size, irrigable (or permeable) area, number of bathrooms, pool ownership and water-using appliance stock become increasingly important with increased disaggregation in cross-sectional and panel data studies. Demographic data from planning authorities and the ABS will provide household occupancy and composition and housing stock figures for geographically defined strata. Occupancy can also be calculated from population and the number of billing accounts (Schneider and Whitlatch 1991). More detailed household data is generally not readily available and has to be collected through household surveys. Dummy variables for geographic location may be used where such specifics are not available or to represent broad features of a locality, such as housing density, soil type and local garden aesthetics.

Econometric models comprising time-series data invariably include weather variables to account for the seasonality and weather sensitivity of demand, in the same vein as climate correction models. Similarly, it may be necessary to account for the effects of changing technology and behaviour, particularly in response to water restrictions (see Section 3.2.1, under ‘Explanatory variables’).

Variable elasticity

The elasticity of a given explanatory variable is defined as the percentage change in the response variable divided by the percentage change in the explanatory variable. In terms of outputs from a linear regression model, the expression is

$$\varepsilon = \frac{dy}{dx} \cdot \frac{x^*}{y^*}$$
$$= \beta \frac{x^*}{y^*}$$

where

ε = elasticity

dy = the change in water demand

dx = the change in the variable of interest

β = the regression coefficient of the variable of interest

x^* = a specific value for the variable of interest on the demand curve (usually the average)

y^* = the specific demand corresponding to x^*

For double logarithmic (Cobb–Douglas function) models (see Appendix 3B), the regression coefficient for the variable directly corresponds to its elasticity. For example, a coefficient of 0.5 means that a 10% change in the variable would result in a 5% change in demand. Log-linear (Stone–Geary utility function) models generate elasticity figures that vary with the average value of the variables themselves, such that higher prices imply greater elasticity. They also allow for a subsistence level of demand irrespective of price, unlike linear models, which implicitly assume that demand will cease beyond a certain threshold in price.

Elasticity is typically classified as in Table 3.6. Price and income have almost universally been found to be relatively inelastic (Arbués et al. 2003, Worthington and Hoffman 2008). Consideration might also be given to distinguishing long-run and short-run elasticities. Prima facie, this distinction could be considered to represent the difference between immediate behavioural water-saving responses to changes in price and longer term structural responses, such as the installation of water-efficient fixtures and appliances (Arbués et al. 2003). However, caution should be applied when using a long-run price or income elasticity in a demand forecast, as the effect may be altered by new water conservation programs.

Table 3.6: Elasticity classification

Elasticity, ε (absolute value)	*Classification*
0	Perfectly inelastic (i.e. non-significant price variable)
0 to 1	Relatively inelastic—the demand response is less than the corresponding change in the variable of interest
1	Unitary elastic—equal percentage changes in price and demand
> 1	Relatively elastic

Estimation techniques

OLS regression is the most common estimation technique used in econometric analysis (Worthington and Hoffman 2008). However, a range of alternative techniques have been employed, primarily to overcome the complication related to block tariff pricing of water. Under block tariff pricing, the price of water both determines, and is endogenously determined by, demand. This feedback relationship can cause OLS regression models to yield biased and inconsistent estimates of the effect of price. To overcome this difficulty, various forms of two- and three-stage least squares regression with instrumental variables have been employed. Details of these alternative forms of estimation are not discussed in this paper but may be found in econometric texts such as Greene (2008). Examples of alternative estimation techniques used in determining price elasticity may be found in Higgs and Worthington (2001), Nieswiadomy and Molina (1991), Hewitt and Hanemann (1995) and Barkatullah (1996).

3.6.2 Examples

There have been countless econometric estimations of urban water demand that both test different model specifications and estimation techniques and derive region- and period-specific price and other elasticities. This section looks at a number of recent Australian examples that are probably more useful precedents in informing new econometric estimations in Australia. Table 3.7 at the end of the section summarises the studies reviewed.

Barkatullah (1996) undertook a study on panel data to predict how changes in the tariff structure influenced water demand in households in the Sydney metropolitan and Wollongong areas. The multipart tariff structure for water price was specified using a marginal price adjusted with a Nordin difference variable. Other household information, such as income, property value, household size, bedrooms, number of bathrooms/toilets and household garden condition, was acquired through a survey conducted by the Independent Pricing and Regulatory Tribunal of NSW (IPART). Both a simple OLS regression model and a two-stage instrumental variable / maximum likelihood model were formulated to estimate household demand over a four-year period. The results revealed a significant bias in the marginal price coefficient from the OLS model. However, the instrumental variable technique was shown to overcome the problem of endogenous price variables and produced a reliable figure for price elasticity.

Three separate studies evaluating the effect of price on demand have been conducted on panel data from Queensland. Higgs and Worthington (2001) evaluated factors influencing a household’s conversion from a fixed rate to a volumetric, user-pays system under a voluntary parallel pricing scheme initiated by the Brisbane City Council. The probability of conversion was predicted using a logit model, based upon variables representing household characteristics including size, income, property value, lot size, the presence of various indoor fixtures, and the extent of outdoor water use. Data on these household variables was acquired from a survey of 350 households in the Brisbane City Council area, along with information indicating whether or not a household had converted to the user-pays plan. Property value was found to be the most significant variable influencing the decision to convert to volumetric charging—households with higher property values were more likely to make the switch. In addition to the logit model, a linear regression model was used to predict household demand, using the marginal price of water in addition to the same set of household variables used in the logit model. Due to the high multicollinearity between variables, 21 of the less significant explanatory variables were consolidated into 10 principal components (uncorrelated variables generated from transformations of the original variables), which were then used in the linear regression model. The final linear regression model was then optimised using least squares regression and a two-stage instrumental variable technique.

Hoffmann et al. (2006) constructed regression models to predict residential demand for households in 53 Brisbane suburbs. Variables for marginal price, lagged consumption, a suburb’s average income and a suburb’s average household size were included in two separate regression models: a linear and a log-log model. The model coefficients were then used to determine short-run and long-run price elasticities. Worthington et al. (2009) used data from 11 local government areas in Queensland to predict monthly water demand. The tariff structures applied within the 11 areas varied considerably, so both marginal and average price specifications were estimated using common, fixed and random effects panel data models. The results indicated a very low price elasticity, perhaps due to suboptimal rate scheduling, and indicated that consumers responded to average price rather than marginal price, partly because of very high service access charges.

Kemp (2004) constructed a regression model of water demand over a year for more than 2600 individual residential customers in Sydney, the Blue Mountains and the Illawarra. The model used cross-sectional data acquired from a survey conducted by IPART in 2003 to break up demand into component uses. The data included information on pool, spa and dishwasher ownership; the number of dual-flush toilets; garden watering hours; yard size; household size; income; geographical location; and whether the household was subject to volumetric charging. The regression model used two interaction terms to model the effect of income on discretionary use and of household size on non-discretionary use. Discretionary use was assumed to be predominantly associated with garden watering, so yard size and the number of garden watering hours were interacted with both income and a variable specifying whether or not the household paid water usage charges. Non-discretionary use was mostly incorporated into the model constant, except for contributions from single-flush toilets. Thus, household size was interacted with the proportion of single-flush toilets in the household. Household size was found to be a key factor influencing demand, with a second person adding 67% to total demand. Higher income was found to increase garden water usage but contributed to a reduction in overall water, an effect that was assumed to be related to willingness and ability to pay for water-efficient appliances. Households that were not required to pay usage charges were found to use more water than those that did pay volumetric fees.

A time-series regression analysis of aggregate daily production data was undertaken by Grafton and Kompas (2007) to explore the possibilities of using pricing instruments to limit demand in Sydney. The price structure for the period (October 2001 to September 2005) was a constant volumetric charge, so price was simply specified in two separate models as nominal and real price. Other variables used in the model were temperature, rainfall and a dummy variable to represent the presence of water restrictions. The model was validated on an out-of-sample dataset, and the calculated price elasticity was then used to extrapolate the changes in price that would have been necessary to maintain water reservoir levels above certain thresholds.

Beatty, O’Brien and Beatty (2006) performed a cross-sectional analysis on consumption of single residential dwellings in Brisbane on a suburb-by-suburb basis. Intersuburb variations were explained using demographic variables including mean lot size, household income, age of the suburb population and household size. Categorical variables for climate zone and the age of the suburb (as a dummy variable indicating whether the suburb was developed in the past 10 years) were also included. The outputs of the regression were used to compare the relative influences of the independent variables on demand. Plots were generated for the demand response to percentage change of each independent variable and for the change in elasticities against percentage change in demand. The analysis found mean income and mean age to have higher elasticities than lot size and household size, although there is no reporting of testing for multicollinearity. Interestingly, the variable response plots indicated non-linear relationships for most of the predictors (income, in particular, exhibited a dramatic exponential effect on demand), which could suggest that the independent variables were transformed prior to the regression.

Table 3.7: Australian examples of econometric estimations of urban water demand

Author	*Location*	*Type of data*	*Price/income specification*	*Method*
Worthington et al. (2009)	Queensland	Panel (region, consumption, monthly)	Marginal price, average price	Linear regression
Grafton & Kompas (2007)	Sydney	Aggregate daily production	Residential water price (definition not presented)	Time series regression
Beatty et al. (2006)	Brisbane	Cross-sectional (suburb, consumption, quarterly)	Average income	OLS regression
Hoffmann et al. (2006)	Brisbane	Panel (suburb, consumption, quarterly)	Marginal price, average income	Regression (linear and log-log)
Kemp (2004)	Sydney, Blue Mountains and Illawarra	Cross-sectional (household, consumption)	Income, income interaction with lot size and watering hours	Linear regression
Higgs & Worthington (2001)	Brisbane	Panel (household, consumption)	Income, marginal price	Logit and linear regression model (optimised using least squares regression and a two-stage instrumental variable technique)
Barkatullah (1996)	Sydney, Wollongong	Panel (household, consumption, quarterly)	Rate structure premium, marginal price, log(income)	OLS regression model and a two-stage instrumental variable / maximum likelihood model

OLS = ordinary least squares.

3.6.3 Pitfalls, limitations and potential solutions

Econometric models are subject to the same problems that can affect climate correction models, including overfitting, multicollinearity and serial correlation of residuals. However, given that the main focus of these models is the elasticity of price and other socioeconomic drivers, the main source of difficulty is the appropriate specification of such variables and the inferences that can be made from the model outputs.

Household income is often correlated with dwelling and lot size, which in turn are positively correlated with demand. Indeed Weber (1989) notes that income may be used as a proxy for lot size and landscaping design. For this reason, caution is essential when making forecasts using an income elasticity derived from an econometric estimation of demand that does not also include household and lot size. Misattribution of correlation is most likely to occur in cross-sectional analysis or in a pooled time-series cross-sectional analysis where a predictor varies over geographical space but is static over time. However, if sufficient data was available to allow a panel data analysis that incorporated a predictor as a time-series variable for each individual cross-section, then inferences regarding the elasticity of the predictor could be considered more reliable. On the other hand, when incorporating potentially correlated variables such as income, lot size and dwelling size in the one regression model, an assessment of multicollinearity and the stability of the model coefficients should be undertaken.

When using elasticities to forecast demand, it is also important to consider the domain of the variables in the calibration period of the regression model. A relationship between an explanatory variable and a response variable is most certain within the ranges of the data that are used to calibrate the model. So, if a model calibration includes demand data that varied within the range 0 and 200 kL/household/quarter and price that varied between $0.50 and $1.50 per kL, then the estimated price elasticity is most reliable within the range of $0.50 – $1.50. Predictions of the demand response to a change in price outside that domain (extrapolation) must be treated with caution, as the relationship between price and demand may no longer hold. Moreover, variable elasticities determined for a given calibration period may not hold outside that period, because the conditions under which they were derived are unlikely to be static (Weber 1989).

The Water Supply Strategy Review undertaken for the Water Board of Sydney (now Sydney Water) (SMEC and SK 1991) provides an example of how extrapolating outside the domain of a model can produce misleading results. In a time-series regression model of annual per capita demand that also incorporated temperature, rainfall and water restrictions variables, (real) household income was found to be positively correlated with demand. When the projections for real income growth were applied to the model along with average rainfall and temperature to generate a long-term forecast, demand was predicted to rise to between 470 and 485 LCD by 2004. In fact, observed demand in 2004 continued a downward trend that started around 1998, dropping well below 400 LCD. A number of errors could have contributed to this result, including misspecification of the income variable leading to an overstated elasticity and assumptions of static or no water restrictions and stationary climate. However, the assumption that the relationship between income and demand (regardless of how flawed the estimation) will continue to hold even a few years into the future is problematic in itself, and in this case led to a significant overestimation of future demand.

The above may also be an example of misinterpreting a statistically significant estimate for a particular variable as an indicator of causality when it is not reflective of reality. As mentioned above, a causal relationship will often be signified by a correlation, but a correlation does not in itself necessarily indicate a causal relationship. For inferences to be made from a model estimate about the effect of a particular variable on demand, there must be an identifiable and (sound) logical relationship between the variable and demand to begin with. Thus, care must be taken to ensure that demand is indeed tied to the variables in question when projecting future demand based on the outputs of a regression model.

3.7 Demographic and land-use analyses

While the econometric analyses described in Section 3.6 can be used to quantify the influence of particular demographic factors (and, less commonly, land-use factors), they are not the only tool used in unpacking the complexities of urban water demand. Analysis of demographic and land-use data in connection with water demand data can provide useful insight in Step 2 of the IRP process (‘Analyse the situation’), as well as helping to develop a targeted response plan in Step 3. Household-level residential demographic studies can provide data that can be used to populate end-use models.

The methodologies used in these analyses are diverse. The main commonality between them is the linking of historical water demand data to demographic data (population characteristics, including age, household size, income level etc.) and land-use data (human and economic activities as defined by geographical boundaries) to tease out usage profiles of particular strata within a supply region. Hence, this section does not include a dedicated subsection covering techniques applied in these types of analyses. Instead, Section 3.71 summarises a selection of various demographic and land-use studies to indicate the range of methodologies that have been applied in the field.

3.7.1 Examples

Birrell et al. (2005) developed a model based on customised 2001 Census data and water utility data from the five major metropolitan centres in Australia to test the effect on demand of different scenarios of household change and urban consolidation. Assuming reduced household per capita water demand with increasing occupancy (second household members using 80% of the amount consumed by reference householders, all others using 50%), the analysis compared demand forecasts based on projections of changes in household structure associated with demographic shifts and urban consolidation with a static per capita forecast based on population growth alone. The study concluded that reduced household occupancy associated with current housing trends and planning is causing a rise in per capita demand and therefore in total residential demand.

Troy et al. (2005) analysed CMDD from 140 census collector districts in the Sydney region characterised according to housing density. They concluded that per capita consumption was ‘for all practical purposes the same’ between detached dwellings, semidetached dwellings and high- and low-rise flats. The implication of this finding was said to be that water conservation policies should seek to curb demand generated by indoor as well as outdoor end-uses.

The East Bay Municipal Utility District (EBMUD) in Oakland, California used planning information as a basis for developing annual demand forecasts to 2040 (EBMUD et al. 2009). Historical water consumption data was entered into a geographic information system (GIS) database arranged according to current and projected land-use polygons (areas with distinct land-use profiles). Base-year land-use unit demands (LUDs) were calculated on a per acre basis from geographically referenced meter data that had been corrected for climatic, economic and demographic factors, and adjusted for unmetered demand. Future demands were predicted by applying adjustment factors to base-year LUDs to account for changes that are expected to occur in the future and multiplying the adjusted LUD by the acreage of land use. It was found that a transition to higher housing densities would result in a net increase in the demand for water.

The above examples examined broader demographic and planning data to understand urban water demand, but it is also sometimes useful to dig deeper to understand demand at the micro level. The NSW Independent Pricing and Regulatory Tribunal regularly conducts demographic studies (based on extensive household surveys of residents in the main urban centres of New South Wales) that are cross-matched with demand data from the corresponding water utilities (IPART 2004b, 2007, 2008). The studies classify households according to their usage levels, geographic location and household characteristics, and identify characteristics, behaviours, fixtures and fittings that are most influential to demand. The analyses incorporate frequency analysis and cross-tabulation of the above elements to develop an understanding of water demand drivers in the residential sector.

A study of high water users in south-east Queensland, which involved a detailed survey of 70 000 households, also looked at household-level data to understand the factors that give rise to high water usage (Turner et al. 2009). Consumption data was linked to household characteristics such as pool ownership; business ownership; appliance and fixture efficiency; lot size; and number and age of occupants. Demographic data from the ABS was also incorporated into the analyses, which involved, among other techniques, frequency analysis, cross-tabulation analysis and sociodemographic profiling. The results were also used to determine water conservation options targeted at high water users to inform future water policy initiatives.

3.7.2 Pitfalls, limitations and potential solutions

When undertaking a demographic study to inform water planning, it is essential to establish clear objectives for how the findings will be incorporated into demand forecasting and options models. The data outputs should be readily transferrable to modelling inputs.

As is the case with econometric estimation studies, demographic analyses are prone to the detection of spurious correlations and to mistaking correlation for causality. This is an artefact of examining aggregated data that can potentially conceal more relevant underlying causal factors. Hence, generating forecasts based on demographic projections alone can be a risky exercise. Given that demographics are only one set of factors among the multitude that influence demand, it is advisable that demographic analysis be used as one of a broader suite of analyses that inform a forecast. In particular, demographic data may be useful both for targeting demand reduction programs and for identifying potential mitigating effects on such programs. Similarly, land-use analyses provide the basis for sector-based forecasts but in isolation do not generate sufficient information upon which to base a forecast for an entire supply region.

Both demographic and land-use analyses must be based on appropriately stratified samples to ensure that the findings can be extrapolated to the broader population. They should also incorporate some form of climate correction, particularly when the analyses could be biased by climatic variability associated with temporal or geographical differences.

3.8 Modelling of behavioural responses to water planning

A significant gap in current demand forecasting approaches relates to the limited description of consumer behaviour. End-use models may have behavioural parameters built into their structure (for example, shower length or frequency), but there is limited scope for addressing behavioural change, and data for such parameters is limited. Agent-based social simulation is a newly developing field that represents a means to simulate consumer behaviour and responses to urban water planning policy and initiatives. The application of agent-based modelling to water demand forecasting is in its infancy, so there is limited precedent or literature to draw from.

3.8.1 Techniques

The goal of agent-based models is to simulate complex interactions between ‘agents’ (entities) in an attempt to determine the overall effect on a larger system. Agent-based models have been used to simulate animal societies, physiological systems, social systems, organisations, economic systems, ecological systems, physical systems, robotic systems and transportation and traffic systems (Davidsson et al. 2007). Agent behaviours such as learning are defined using sets of rules, which can be adaptive or fixed, stochastic or deterministic, complex or simple (Billari et al. 2006). Such rules influence the interaction between agents during an iterative process that ultimately leads to system adaption. Computers have enabled agent-based models to simulate complex systems comprising multiple agents interacting with each other and the environment. Although agent-based modelling software packages have been developed, they have rarely been used for academic purposes. Instead, models have generally been constructed using an ordinary programming language (Davidsson et al. 2007).

In the field of urban water planning, agent-based modelling has been used to simulate complex social interactions between consumers and demand-management policy instruments such as water pricing, public awareness campaigns and urban water trading. Agent-based models often require the input of other models (such as econometric, end-use and GIS models) and may form part of a broader modelling framework or decision support system. Essentially, they are an expansion of the ‘bottom-up’ approach of end-use modelling in which demand is modelled at an individual level (rather than aggregated across a sector) and is determined dynamically by behavioural choices related to water use (for example, the installation and use of a particular type of water technology). Choice is driven by prevailing conditions (climate, price, regulations etc.), personal attitude and mechanisms of social interaction.

Along with consumer agents, these models typically include agents to represent water utilities, water regulators and other stakeholders in the water industry. The means of defining agents vary with the purpose of the study and with data availability. Consumer agents are generally defined according to their attitude towards water conservation, their position within a social network and an initial demand profile (based on end-use and/or econometric analyses), which changes over the course of the simulation. Utilities have been characterised by such features as water availability and supply capacity, supply costs, and rules governing the setting of price. Meteorologist agents can be used to input climatic data into the model where there are elements of consumer or other agent behaviour that are weather-sensitive.

3.8.2 Examples

Rixon et al. (2007) explored the effects of tariff structures and water resource depletion on water demand using two separate agent-based models capable of representing social interactions and their influence on water conservation behaviour. The first model was relatively simple, exploring the effects of fixed and variable tariff structures on water demand and utility profits using both a randomly generated social network and a ‘real’ social network. However, there were a number of perceived limitations associated with the simplistic model. Not only did it produce unrealistically low daily demands, it was also limited to small communities and failed to adequately define how beliefs may influence water conservation behaviour.

The limitations of the first model led to the construction of a second model, which used the concept of memetics to explore how imitation influences water consumption behaviour. In the model, water-saving devices and behaviours were represented by a total of 10 memes (cultural ideas, symbols or practices passed on through imitation). The memes were propagated within a hypothetical social network, allowing the effect of depleting water resources on water conservation behaviour to be evaluated. Unlike the simpler preceding model, the water memes model produced relatively realistic water demands, displaying the expected seasonal variability. However, future empirical studies on 'imitation behaviour' were perceived to be necessary for more effective calibration and validation of this model.

Athanasiadis et al. (2005) assessed the ability of a hybrid model, known as DAWN, to evaluate the effect of various water-pricing policies on residential water demand using data obtained from Thessaloniki, Greece. DAWN is a hybrid model, incorporating conventional econometric models with an agent-based social model. The agent-based component of the model effectively allowed the representation of social interactions between consumers deemed to significantly influence water conservation behaviour. Unlike the study by Rixon et al. (2007), the social interaction component of the model constructed by Athanasiadis et al. used results from a questionnaire to define parameters for the model. In particular, the proportions of four typical consumer types were calculated and subsequently used to determine the propagation of water conservation beliefs within a community. This was deemed to result in greater confidence in model forecasts, which were in fact comparable to both the conventional econometric approach and actual values. A similar approach was adopted by Perugini et al. (2008) in their analysis of the impact of urban water trading on households in Adelaide.

Ernst et al. (2005) integrated an agent-based component within a large decision support system (DSS) used to manage water resources in the upper Danube basin. Five major components were incorporated in the DSS: atmosphere, land surface, river network, groundwater and actors, each of which was defined using as many as six different models. The actor component comprised models for households, water supply, the economy, demography and tourism. Domestic habitual water-related behaviour was initially modelled via a 'shallow model', which used 25 different household types (separated based on income and household size) to model the 10 major end-uses (laundry machines, showers etc.). This model was then expanded to create a 'deep model', which integrated the conscious decision-making process behind water conservation behaviours with habitual water-use decision making. The population was first separated into 10 predefined social groups known as 'milieus', each having distinct beliefs and lifestyles. Agent-based modelling was then used to simulate the transfer of water-saving innovations throughout spatially constructed social networks in response to externalities, such as the environment. A scenario run was undertaken on a prototype model, simulating the response of two milieus ('traditionals' and 'post-materialists') to the reporting of water scarcity under dry climate conditions over a projected 30-year period.

Table 3.8 summarises the key features of each of the agent-based models described above.

Table 3.8: Examples of agent-based modelling of water demand

Author	*Location*	*Agents*	*Consumer attitudes*	*Demand profile*
Perugini et al. (2008)	Adelaide	Consumers, water authority	High, medium and low water users	Assumed elasticities
Rixon et al. (2007)	Australia, using artificial data	Consumers, water utility	Water savers, water utilitarians	Assumed elasticities
Athanasiadis et al. (2005)	Thessaloniki, Greece	Consumers, water utility, meteorologist, simulator	Opinion leaders, socially apathetic, opinion seekers, opinion receivers	Econometric model
Ernst et al. (2005)	Upper Danube Basin, Germany	Consumers, water suppliers	Milieus (10 sociological groups), (traditionals, post-materialists)	End-use model with assumed price elasticity

3.8.3 Pitfalls and limitations

One of the main advantages of agent-based modelling is the capacity to incorporate behavioural information into a water demand modelling framework. In this manner, the effectiveness of various water conservation programs may be evaluated. One of the major disadvantages of agent-based modelling, however, is related to the collection of accurate behavioural data. Such data is generally not readily available, requiring potentially expensive market research studies to inform a given project. In the absence of such data, a variety of assumptions must be made during model development, leading to potentially erroneous models. As a result, agent-based models may be deemed to 'provide a false sense of realism' (Rixon et al. 2007:79).

To overcome this limitation, Rixon et al. (2007) suggest that models should remain as simplistic as possible in order to help locate potential sources of errors and evaluate various model assumptions. Indeed, simple micro-level dynamics are held to be capable of generating complex patterns at the macro level (Billari et al. 2006). In this vein, Perugini et al. (2008) used relatively simple demographic groups to define household consumer agents in their investigation of the complex interactions involved in urban water trading. Rixon et al. (2007) also contend that, while absolute validation of an agent-based model is virtually impossible, sensitivity analyses can be used to gain insight into the robustness of the model.

Despite the various precautions that may be taken, it is often found that the use of agent-based models in a predictive capacity is fraught with difficulties. For this reason, agent-based models have mainly been used to explore the implications of various water conservation scenarios (as by Ernst et al. 2005 and Perugini et al. 2008), rather than for generating accurate predictions of water demand.

3.9 Building an integrated demand forecast

While the analytical techniques outlined in the preceding sections are generally highly developed and widely used, it is not always clear how they might be incorporated into a broader demand forecasting process. Indeed, in many of the published studies that employ these techniques, particularly econometric analyses, they are reported in isolation and only limited reference is made to the broader urban water planning process. However, a number of urban water planning frameworks being used in Australia locate complementary urban water demand analysis techniques within an urban water forecasting and planning framework.

The *Guide to demand management and integrated resource planning for urban water* (Turner et al. 2010) describes an IRP framework (see Appendix 3A) for which there is a companion end-use and options development model called the integrated supply–demand planning (iSDP) model. The iSDP model, which was developed by Sydney Water Corporation and is now under the auspices of the WSAA, integrates end-use and sector-based demand forecasting techniques for the residential, non-residential and non-revenue water sectors, as well as incorporating the impacts of defined demand management, source substitution and supply options. In the discussion on demand forecasting techniques, the guide points out the need to:

- identify an appropriate climate-neutral year (not affected by climatic extremes) against which to calibrate the residential end-use component of the iSDP
- incorporate some form of analysis (regression is suggested) to determine 'how previous interventions such as user pays pricing, restrictions, a water efficiency program or replacement/calibration of bulk water meters' may have affected demand.

There has been only limited discussion on the techniques available for performing these tasks (hence, the development of this resource paper).

The Demand Side Management Decision Support System, or DSM DSS (DEUS 2006), was developed to 'facilitate the rapid development of demand forecasts and preliminary evaluation of demand management measures' in regional New South Wales. It comprises an end-use model with simplified inputs and assumed breakdowns of particular end-uses, and is capable of performing a scenario-based analysis of demand-management options. The model requires inputs of current total and sectoral demand, and it is recommended that all data entered be 'corrected for the influence of climate', using the IWCM Water Demand Trend Tracking and Climate Correction model (DEUS 2002). To simplify the process of developing forecasts, the DSM DSS uses in-built assumptions that are essentially designed to negate the need to perform the types of analyses described in this paper. The assumptions relate to the effects of a range of water conservation programs, including federal and state regulations related to water efficiency, residential retrofits, rainwater tanks, dual reticulation, community education, water restrictions, user-pays water pricing, leak detection and repair, non-residential water audits, and audits of evaporative cooling units and cooling towers. For example, water restrictions are assumed to achieve a 10% reduction in external water use among participants, while water price is assumed to have an elasticity of –0.2. Assumptions used to generate the effects of the various demand-management options are not provided.

The integrated water resources planning framework described in Beatty et al. (2007a) is a multitiered urban demand forecasting framework comprising climate correction of BWPD, sectoral analysis and cross-sectional analysis of customer meter demand, and end-use analysis. To generate a hydrologic water balance model, an OLS regression model of daily BWPD is used to generate a daily index. This, combined with a random noise component, forms the seasonal component of the forecast, while the non-seasonal component of demand is determined using the end-use model. Climate correction and sectoral and cross-sectional analysis are used to determine the impacts of water restrictions and pricing and the elasticities of other factors such as income and lot size, although no detail is provided on how those impacts are then incorporated into the ultimate demand forecast.

While many of the analytical studies given as examples in the preceding sections did not extend to developing a long-term forecast of demand, there are examples of using climate correction-type regression models, econometric models and demographic and land-use models to generate long-term forecasts. Grafton and Kompas (2007) used a time-series model to determine a price elasticity for Sydney and explore the price rises necessary to maintain dam levels above a range of thresholds. The elasticity figure was then used to project dam levels under four scenarios of alternative supply and price controls assuming recent inflow patterns. EBMUD developed long-term forecasts based on land-use projections and climate-corrected demand figures (EBMUD et al. 2009). Athanasiadis et al. (2005) and Perugini et al. (2008) integrated conventional econometric models (for price elasticity) with agent-based social models to forecast water consumption under different policymaking and water-trading scenarios. Aside from the EBMUD study, however, these studies do not appear to directly contribute to water planning outcomes, but focus more on the exploration of policy options. And without accommodating the full spectrum of demand drivers in the analyses, the accuracy of the forecasts generated in these studies remains in question.

In summary, there are a number of established demand forecasting frameworks that incorporate or accommodate complementary analyses in the forecasting process, but information on the methods, application and integration of those analyses is limited. There have also been attempts to use some of the complementary analytical techniques described in this paper to develop long-term forecasts of demand that sit in isolation from urban water planning, strategic or otherwise. This paper aims to provide the necessary information to understand and piece together the various analytical techniques available and how and where they have been or can be used to inform demand analysis and forecasting. Many of the techniques described use standard BWPD and/or CMDD as well as BoM data. However, some require more detailed data that may be difficult or prohibitively expensive to obtain.

Before embarking on any data analysis exercise, it will be essential to understand the quality of the data at hand, what additional data is needed, and the skills and time available. Above all, it will be essential to clarify the purpose of the analysis and which technique is most appropriate given other constraints and fits best with the planning framework being used.

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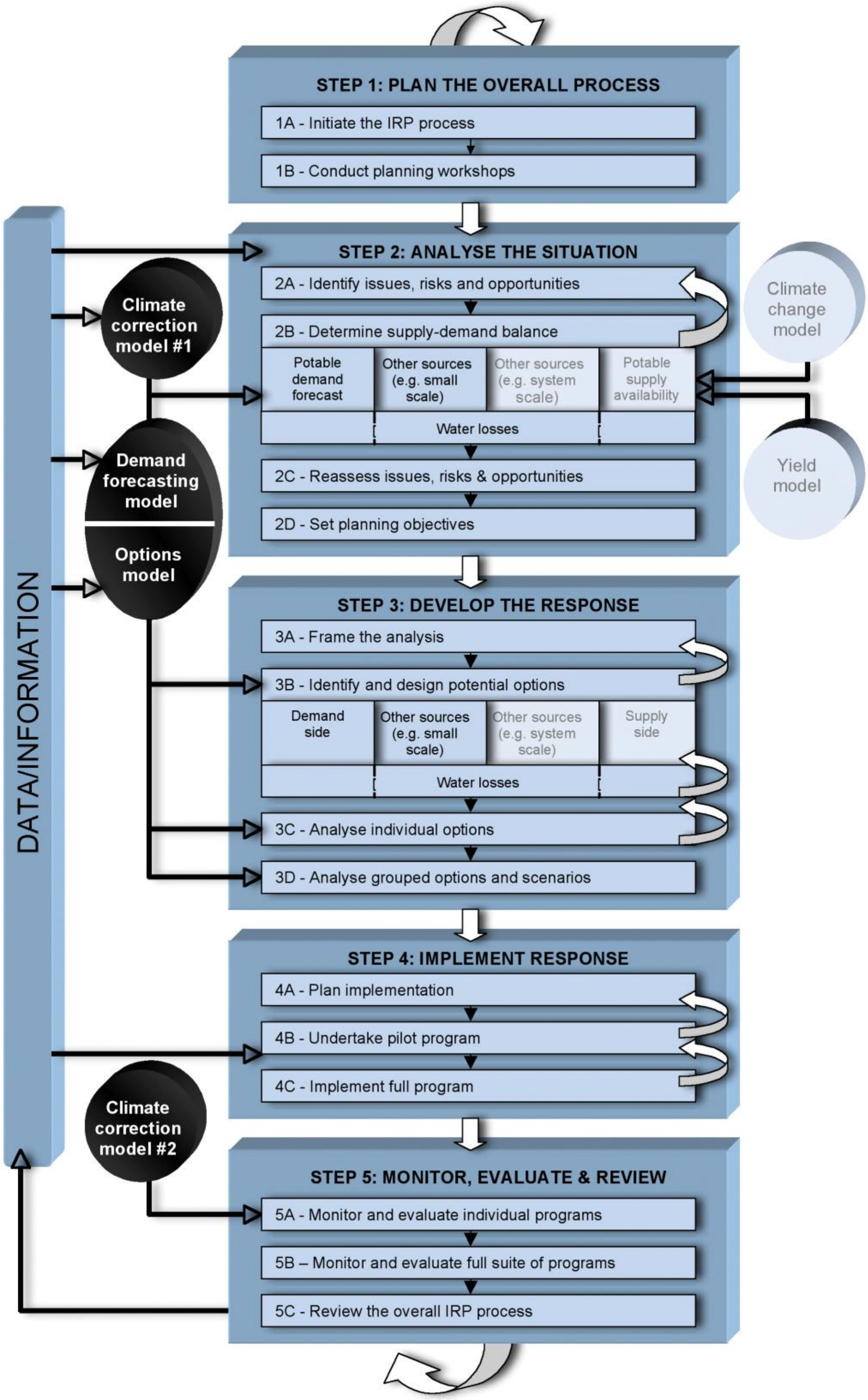
Appendix 3A The IRP framework



Source: Turner et al. (2010)

Appendix 3B Regression modelling of water demand

Ordinary least squares (OLS) regression is one of the most widely used techniques in the analysis of historical water demand. It is a tool used in climate correction, short-term forecasting, econometric estimation and evaluations of water conservation programs and other demand reduction strategies. With water demand being the response variable, the independent variables common to most regression models are various forms of and combinations of meteorological variables, such as temperature, rainfall and evaporation. These variables are primarily used to describe weather-induced variability in demand, but they are also able to describe the underlying seasonality of water demand. However, other variables such as Fourier series and monthly or seasonal dummy variables may also be employed to describe seasonality. Other non-climate factors that are typically incorporated into water demand regression models include water price, water restrictions, water conservation programs and various sociodemographic and household data. The following discusses some of the main considerations that should be addressed when embarking on a water demand regression modelling exercise.

3B.1 General form of regression models

The simplest regression model used to estimate water demand is the basic linear regression model. An OLS regression model takes the general form:

$$y_t = \beta_0 + \sum_{i=1}^{n} \beta_i \, x_{i,t} + \varepsilon_t \quad 2$$

where

y_t = the response variable at time t

x_{it} = the i^{th} explanatory variable at time t

n = the number of explanatory variables (weather/season, water restrictions, water price etc.)

β_i = the regression coefficient associated with the i^{th} explanatory variable

β_0 = the intercept

ε = the error term at time t.

Other methods may be used to derive the coefficients of simple linear regression models, such as generalised least squares regression. Alternatively, variables may be transformed and nonlinear models constructed (see Section 3B.8).

3B.2 Explanatory variable selection

There are potentially a large number of variables capable of explaining variation in water demand. However, many of those variables may be classified as ‘secondary variables’ not capable of directly defining fundamental processes. Furthermore, many variables are potentially correlated with one another, describing similar portions of variability in the dependent variable. As a result, it may be possible to derive numerous, comparably valid regression models, using different combinations of explanatory variables.

A number of approaches may be used to select a set of explanatory variables for a linear regression model. Some models will have default variables that are the focus of the analysis, such as price or water conservation program participation. Weather/seasonal variables tend to be universal inclusions to demand models, although the selection of an appropriate combination of those variables is not always straightforward. In the first instance, a modeller may select a set of variables based upon a theoretical understanding of the factors that may influence water demand. In many situations, however, the effect of weather variables on water demand will be highly dependent on the data domain (that is, the region) analysed. For example, rainfall can be highly influential in some areas and have very limited effect in others.

Therefore, a strong understanding of the regional context is important in setting up the analysis.

Correlation between variables such as temperature and evaporation can lead to a situation in which a variable that appears highly correlated with water demand may not explain additional variability in water demand (that is, variability not previously explained by variables already included in the model). This problem may be overcome by viewing a correlation matrix to avoid using multiple combinations of highly correlated variables in a model, or by using automated techniques for entering variables into a linear regression model, such as forwards, backwards and stepwise regression. When using automated techniques for entering variables into linear regression models, it may be important to view the signs of the associated regression coefficients to ensure that the final model is 'intuitively correct'. This helps to ensure that variables do not model sporadic variability in the dependent variable.

A selection from the variables mentioned above will often be sufficient to build a satisfactory time series regression model. When undertaking cross-sectional or pooled time series cross-sectional regression modelling, the variables that may be included will vary depending on the strata used to define cross-sections and may include such factors as income and other household characteristics, such as occupancy and lot size. When looking at the individual household level of strata, more detailed characteristics such as appliance and fixture ownership and behavioural variables might be included. Essentially, the availability of data will ultimately determine which variables are included in these more detailed models.

3B.3 Data preparation

Regression models of water demand typically use demand data normalised by population, number of dwellings or another demographic unit appropriate to the sector. This obviates the need to use an independent variable to represent population growth within the model (Weber 1989). Demand data is also often expressed on a per day basis to remove the effect of different lengths of months and leap years.

Processing of data for other variables will depend on the variable specification and the quality of the data. Meteorological data often contains missing or poor quality data. Price variables tend to have to be calculated when the tariff includes a volumetric component. Sociodemographic data to be used in cross-sectional and pooled time series cross-sectional analyses may need to be linked to the strata of interest, distributed across the time steps of the model, or both.

3B.4 Data screening

It is not uncommon for demand records to contain erroneous data, whether from measurement error or inaccuracy or from incorrect data entry. Simple tests can be applied to identify bad data points. BWPD can be compared with the physical capacity of the water treatment plants that supply the water or the pumping capacity of the distribution network. Logical outlier thresholds can be set, such as daily production exceeding average monthly production or quarterly metered consumption exceeding average annual consumption. Alternatively, statistical tests can be applied to identify outliers, such as those points that are 2.5 times the standard deviation above the mean (for normally distributed or log-transformed data) or 1.5 times the interquartile range above the third quartile.

The supplier of the data should be consulted to identify the source of the errors and to make an appropriate choice between eliminating, adjusting or imputing the data in question. A balance also needs to be found between the potentially competing needs of eliminating bias from an analysis and retaining sufficient data to perform the analysis.

3B.5 Model time step and data binning

Regression models predicting water demand are most often based on time series data. Thus, the time step associated with each data point is a critical consideration. Using daily data has the twofold advantage of providing more data points and greater variance to fit the model against (that is, a broader range against which to fit explanatory variables). The difficulty with daily data is that it can be less reliable (in terms of integrity) and that the multitude of other factors that influence demand on a day-to-day basis contribute to significant data 'noise', which is difficult to capture in a model limited to broad explanatory variables. Larger sub-annual time steps (for example, fortnightly or monthly) work on data with less noise and thus tend to produce stronger fits that are easier to interpret graphically. However, the smaller number of data points constrains the number of variables that can be used in the regression, and additional care must be taken to avoid model overspecification.

The attempt to capture the effect of weekends and holidays on demand provides an illustrative example of the relative advantages and disadvantages of different modelling time steps. Residential demand has been observed to increase substantially over weekends and holidays. A daily time-step model calibrated to a year of data will have adequate data points and thus degrees of freedom to allow a variable or set of variables to account for this. However, weekend or holiday demand responses may not be consistent over time and the variable may only explain some of the observed variability associated with weekends and holidays. Moreover, only BWPD records are available at a daily time step, meaning that the climate correction formulated from the model outputs may not be directly applicable to the residential sector.[5] A weekly time-step will effectively smooth out the effect of weekends, but may require a variable or a set of variables to take account of holidays, and again can only be applied to bulk water data. A fortnightly or monthly model will generally smooth out both weekend and holiday effects. The reduced number of data points for each, however, may require a longer calibration window, especially if other factors such as restrictions need to be accommodated.

Ultimately the time step used in the model is governed by the time step of the available demand data. Production data is often recorded daily, while customer meter data is usually recorded on a quarterly or six-monthly basis. A monthly model is generally the finest resolution of time step that can be applied to quarterly data, assuming an appropriate binning technique is applied (see Appendix A of Turner et al. 2010), although attempts have been made to produce finer time steps from customer meter data (Moglia et al. 2009). Daily production data can be used in a daily model directly or can be binned to create larger time steps if desired. Table 3B.1 lists the data and time steps used in various time series regression models of aggregate water demand.

[5] An artificial daily time series could theoretically be generated from quarterly customer meter data (as suggested in Moglia et al. 2009), although the smoothing effect of this process will render weekend and holiday variables ineffectual.

Table 3B.1: Examples of types of data, time steps and model forms and used in regression modelling of water demand

Study	*Demand data*	*Time step*	*Model form*
Anderson, Miller & Washburn (1980)	Total daily production	Daily	Linear
Hansen & Narayanan (1981)	Monthly production expressed as volume per active service connection per day	Monthly	Log-log
White, Lovell & Young (2000)	Daily production per capita	Daily	Linear
Sarac & White (2001)	Daily production per capita	Daily	Nonlinear
Maheepala (2003)	Summed daily production per capita	Monthly	Linear
Kidson, Spaninks & Wang (2006)	Total production	Monthly	Linear
Maheepala & Roberts (2006)	Daily production per capita	Daily	Linear
Beatty, O'Brien & Beatty (2006)	Annual consumption per property	Yearly	Nonlinear
Grafton & Kompas (2007)	Total daily production	Daily	Nonlinear
Beatty et al. (2007b)	Quarterly customer meter per account Monthly production expressed as volume per capita per day	Quarterly Daily	Nonlinear
Beatty, Roberts & Beatty (2008)	Quarterly customer meter per account Daily production per capita	Quarterly Daily	Nonlinear
Moglia, Grant & Inman (2009)	Quarterly customer meter per property	Monthly (binned)	Linear

3B.6 Specification of explanatory variables

The way an explanatory variable is specified will in part determine its effect on the final model. For example, temperature may be expressed as daily maximum, minimum or mean temperature, or as the number of days within a time step above or below a certain threshold. The simple occurrence of rainfall has been observed to be more influential on demand than the magnitude of the rainfall (Maidment and Miaou 1986) and hence the number of rain days may be more significant than the amount of rain. The selection of a particular specification of a variable will be region-specific, and several options may need to be explored to find the variable with the most explanatory power. It should be noted too that some weather variables are likely to be highly correlated (for example, temperature and evaporation). Inclusion of correlated explanatory variables in a regression model leads to problems of multicollinearity (see Section 3B.9). In this case, it may be necessary to exclude one or more correlated variables from the analysis or to consider alternative specifications of those variables.

Independent variables may be normalised against the long-term average (by subtracting the long-term average and dividing by the standard deviation—similar to calculating the z-score) so as to model the effect on water demand of departures from average conditions. Normalising the data allows direct comparison between the regression coefficients so as to determine the relative influence of each variable on demand. Most contemporary statistical packages used to perform linear regression modelling provide an option to determine standardised model coefficients along with conventional coefficients. Standardised coefficients are derived using normalised data; however, in this case the data is normalised to the average within the modelling period rather than a long-term historical average. It is also possible to normalise weather variables to *monthly* long-term averages (as opposed to a single long-term average). This approach to normalisation effectively removes the seasonality of weather variables. Therefore, a subsequent model is best formulated with some form of seasonal adjustment as described in Section 3B.7.

Climate correction regression models will generally produce strong results with a minimum number of variables (no more than four or five for a baseline period unaffected by restrictions or other demand management), as much of the variation observed in water consumption (more than 80%) can be explained by variables that reflect seasonality, such as temperature

(Weber 1993). It is common, however, and particularly so in Australia, for demand to have a particular seasonal profile that is not adequately explained by weather variables alone. To overcome this, some studies have developed separate equations (models) for distinct seasons, for example growing and non-growing periods (Hansen and Narayanan 1981). Alternatively, the response data or the regression model may be adjusted for seasonality (see Section 3B.7).

Ultimately the selection of the explanatory variables and their respective forms should be guided by a logical interpretation of the relationship between the variable of interest and water demand, or at least justified by such reasoning. Table 3B.2 lists the weather variable specifications previously used in regression models of water demand.

Table 3B.2: Examples of specifications of weather variables used in regression models of water demand

Explanatory variable	*Form*	*Example references*
Temperature (T)	Mean daily maximum	Maheepala & Roberts (2006) Kenney et al. (2008) Kidson et al. (2006) Dziegielewski et al. (1992) Grafton & Kompas (2007) Anderson et al. (1980) Hansen & Narayanan (1981) Danielson (1979)
	Broken-line function using daily maximum	Maheepala & Roberts (2006)
	No. days above a threshold	Turner et al. (2008a)
	No. of cooling degree days	Dziegielewski et al. (1992)
Rainfall or precipitation (P)	Sum or total	Hansen & Narayanan (1981) Kenney et al. (2008) Kidson et al. (2006) Renwick & Archibald (1998) Dziegielewski et al. (1992) Grafton & Kompas (2007) Maheepala(2003)
	No. of days above a threshold	Dziegielewski et al. (1992)
	Average (where time step > 1 day)	Danielson (1979)
	Effective precipitation $ER_1 = P_t - 0.1$ $(0.1 \leq P_t \leq 0.6)$ inches $ER_2 = \alpha P_t + (1-\alpha) P_{t-1}$ $(\alpha = 0.4, P_t \leq 1, ER_{2\,t} \geq 0)$ inches	Anderson et al. (1980)
Solar radiation or sunshine hours	Solar radiation (S)	Anderson et al. (1980)
	Daylight hours	Hansen & Narayanan (1981)
Evaporation (E) or evapotranspiration (ET)	Modelled using T and S	Anderson et al. (1980)
	Modelled using P and T	DEUS (2002)
	Sum or total	Maheepala (2003) Kidson et al. (2006)
Combined E or ET and P	Difference between E and P	Anderson et al. (1980)
	Difference between ET and P	Agthe & Billings (1980) Anderson et al. (1980)

Adjusting for seasonality

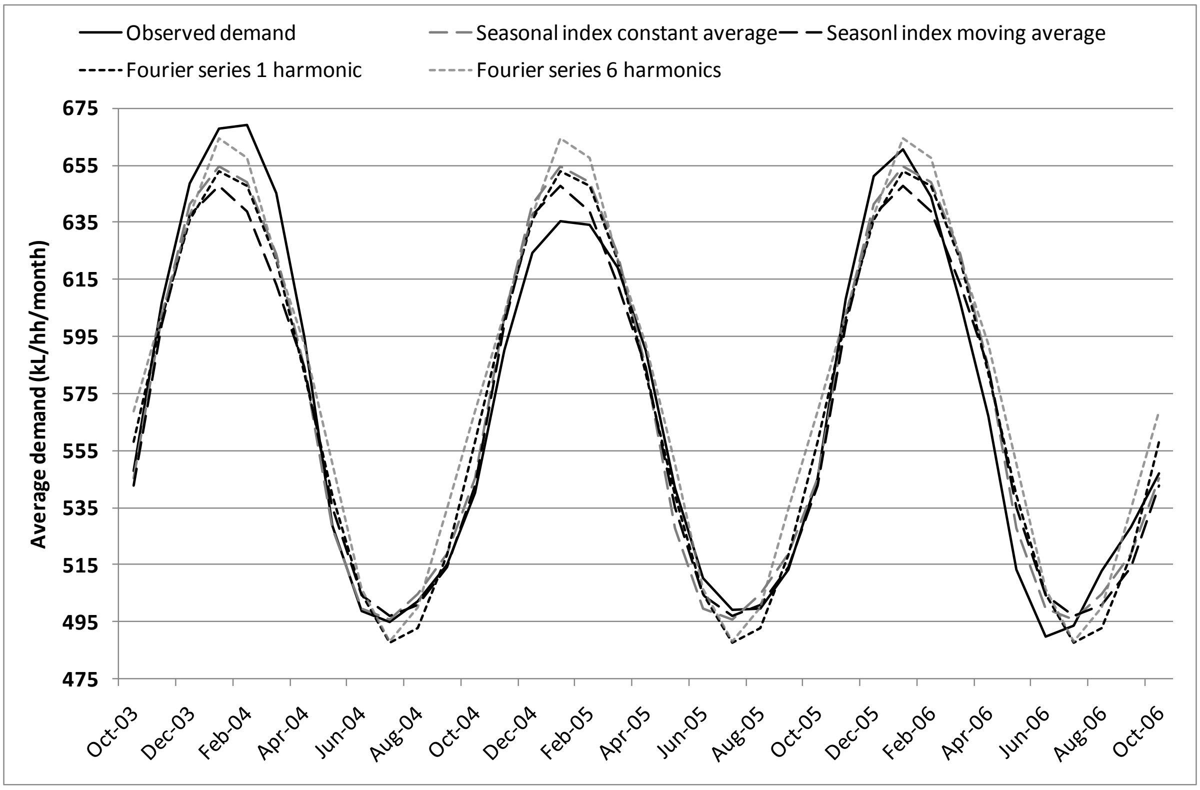
Urban water demand in Australia, particularly that of single residential households, often exhibits a strong seasonal pattern that is not adequately reflected in the seasonality of weather variables alone. Most probably, this will be due to a strong dichotomy between summer and winter demand responses and an inability of weather variables to efficiently describe associated spring and autumn transition periods (Weber 1989). When this is the case, an underlying seasonal profile of demand can be derived, such that weather variables act to explain departures from typical seasonality rather than directly describe the seasonality. The seasonal profile of demand can either be removed from the response variable prior to performing a regression analysis, or it can be incorporated into the regression model using explanatory variables.

The first technique, typically called 'deseasonalisation', involves deriving an additive or multiplicative index for each calendar month (seasonal effect) based on a constant average or yearly averages where there is no discernible trend in demand over time, or a moving average where a trend is apparent (see Bowerman et al. 2005, Chatfield 2004 or other time series analysis texts for details). The 12 indices are then applied to the time series of observed demand by dividing each month's observed demand by the corresponding seasonal index, effectively eliminating the seasonal component. A subsequent regression model of the deseasonalised data thus considers only the variability associated with atypical weather and other non-seasonal factors. Before performing a regression on deseasonalised demand data, however, a test for stationarity (for example, the augmented Fuller–Dickey test) should be run to ensure that the data will produce meaningful sample statistics such as means, variances, and correlations with other variables that would inform a regression model.

Alternatively, seasonality effects can be expressed in an explanatory variable in the regression model itself. The seasonal index described above can be used as a continuous explanatory variable in the regression (Dziegielewski et al. 1992, Maddaus 2007) instead of for transforming the demand data. Another specification of seasonality is to use a set of dummy variables that represent the month, the bimonthly period or the season. This specification requires a reference case, meaning that only n – 1 dummy variables need be specified, where n is the number of monthly, bimonthly or quarterly periods (using n dummies will result in perfect multicollinearity). A Fourier series specification of seasonality is a set of sine and cosine terms that generates a sinusoidal function (see Dziegielewski et al. 1992; Gato et al. 2007a; Zhou et al. 2002). Typically a Fourier series of water demand needs to use only two or fewer harmonics, although up to six may be used on an annual cycle reflecting monthly variation. Care should be taken when using multiple seasonal effect variables so as to not overspecify the regression model, particularly when using monthly data.

The seasonal index approach is perhaps the most elegant of the abovementioned options for seasonal decomposition. It minimises the number of explanatory variables needed in the regression and effectively detects nuances such as constant demand over winter or spikes or dips in particular months of the year. However, ideally at least 10 years of data is required to formulate a reliable index (Maddaus 2007). Moreover, the index should be derived from historical data that is relatively unaffected by other factors, such as price regime changes, water restrictions and other demand-management actions. Using monthly dummy variables in a regression model produces essentially the same result as a seasonal index generated from a static net average; however, it reduces the power of the regression by adding explanatory variables. Hence, using dummy variables to indicate season (rather than month) may be more appropriate when using dummy variables in a monthly time-step model. A comparison between demand predictions using different seasonal adjustment techniques is presented in Figure 3B.1.

Figure 3B.1: Seasonal adjustment using different forms of seasonal indexes and Fourier series



Non-linear relationships

Almost universally, urban water demand data is not distributed normally; it typically displays a positive skew, bounded by zero to the left and a large tail to the right. When non-normality is also apparent in the residuals of a regression model, one of the fundamental assumptions of linear regression is violated (see Section 3B.9). Also problematic to linear regression is the fact that relationships between demand and meteorological conditions are often non-linear. Generally, the problems of non-normally distributed residuals and non-linear relationships are overcome by log transforming the demand data, or by using a multiplicative model form, which involves applying a log transformation to both the demand (the dependent variable) and the independent variables.

The functional form of the log-log regression model is as follows:

$$log(y_t) = \beta_0 + \sum_{i=1}^{n} \beta_i \, log(x_{i,t}) \qquad 3$$

Retransforming equation 3:

$$y_t = 10^{\beta_0} \, x_{1,t}^{\beta_1} \, x_{2,t}^{\beta_2} \ldots x_{n,t}^{\beta_n} \quad 4$$

where

$x_{1,t}$ = the 1st explanatory variable at time t

$x_{2,t}$ = the 2nd explanatory variable at time t

$x_{n,t}$ = the nth explanatory variable at time t

β_1 = the regression coefficient associated with the 1st explanatory variable

β_2 = the regression coefficient associated with the 2nd explanatory variable

β_n = the regression coefficient associated with the n[th] explanatory variable.

The residuals of the log-log model are assumed to be multiplicative, allowing for the commonly observed phenomena in which the errors associated with predictions of water demand increase as water demand itself increases. This helps to limit the leverage effect of outliers and to produce constant variance in the residuals to ensure that the fundamental assumption of homogeneity of residual variance is not violated. It is important to be aware, however, that a limitation of log-transformed models is that they tend to underpredict higher values.

Alternatively, just the response variable may be logarithmically transformed and linearly regressed against the untransformed explanatory variables to form a semi-log model.

$$log(y_t) = \beta_0 + \sum_{i=1}^{n} \beta_i \, x_{i,t} \qquad 5$$

Retransforming equation 5:

$$y_t = 10^{(\beta_0 + \beta_1 x_{1,t} + \beta_2 x_{2,t} + \ldots + \beta_n x_{n,t})} \qquad 6$$

The advantage of these two types of models is that simplistic linear regression procedures may be applied once the data has been transformed.

It is widely acknowledged that relationships between weather variables and demand are often non-linear, causing models using raw weather data to perform poorly or even violate the critical assumptions of regression modelling (see Section 3B.9). To overcome this problem, variables can be transformed to better reflect their relationship with demand. For example, temperature might not trigger an observable demand response unless it climbs above a certain threshold. Conversely, the response to rainfall could be curvilinear up to a certain limit and constant above it. To account for such non-linear relationships, a range of transformations may be employed, such as step, broken-line (see Zhou et al. 2001), logarithmic (select individual explanatory variables as opposed to all), asymptotic, power and arctan (see DEUS 2002) functions. The regression model equation then becomes:

$$Y_t = \beta_0 + \sum_{i=1}^{n} \beta_i \, f_i(x_{i,t}) + \varepsilon_t \qquad 7$$

where

Y_t = observed demand at time *t*

β_0 = model intercept

β_i = regression coefficients

$x_{i,t}$ = explanatory variable at time *t*

$f_i(x_{i,t})$ = non-linear function of $x_{i,t}$

or

$f_i(x_{i,t})$ = $x_{i,t}$ (when linear)

ε = error term.

DEUS (2002) developed a synthetic variable called the soil moisture index (SMI) that was calculated from rainfall and evaporation data to describe the condition of the soil in residential gardens. It acts as a proxy for irrigation demand by providing a ‘memory’ for previous rainfall and evaporation, to help better characterise demand response to weather. The variable is essentially an approximation of plant-available soil water that acts as a storage reservoir for recent rainfall. The parameters of the variable are determined through a least squares fit prior to the variable being used in a regression. Zhou et al. (2000) also incorporated model effects for soil water storage into a daily demand regression model. They specified a variable for the number of days since the previous rainfall event and an antecedent precipitation index (a variable representing net rainfall that includes a lag term and an assumed corresponding loss factor). Variables that attempt to capture the soil reservoir effect are generally only applicable to daily time-step models. The error associated with the fitting parameters to these (semi-)synthetic variables should also be reported and incorporated into the final model.

Caution should be exercised when applying transformations that create additional fitted parameters (that are used to optimise the transformation function), as it can lead to model overspecification. For simplicity, the more general log-log or log-linear transformations, which can accommodate a wide range of non-linear relationships, may be preferable because they do not require fitting of transform function parameters.

3B.7 Checking model assumptions and validity

There are four key assumptions behind any regression model, all related to the model residuals (the difference between predicted and observed response data):

- zero mean
- constant variance
- normal distribution
- independence.

Essentially, the variance and distribution of residuals may be considered to be indicators of the level of bias within the model. If a model is sound, its residuals should reflect the random 'white noise' of the data and show no discernible pattern, trend or constancy.

The first assumption requires the mean of the residuals to be equal to zero for all values of the independent variable/s, while the second assumption requires the variance to be constant for all these values. The validity of the second assumption may be checked by viewing plots of residuals against independent variables, predicted values and time (for time series data). If the assumption holds, the plotted residuals should fluctuate within a constant band either side of zero. Fanning out to the right indicates increasing error variance, while funnelling in to the left indicates decreasing error variance. Both of these types of fluctuations negate the ability to make statistical inferences from the model. Non-constant variance, or heteroscedasticity, can sometimes be overcome by transforming the response variable using a logarithmic or power function. Alternatively, non-constant variance may suggest that the functional form of the model is incorrect, indicating the need for an additional variable in the regression model or a suitable transformation of one or more explanatory variables already included in the model.

Adherence to the assumption of a normal distribution of residuals may be determined by simply viewing a stem-and-leaf display or histogram of the residuals. Normality is deemed to hold when these plots appear bell shaped and centred about zero. Alternatively, more rigorous statistical tests may be performed on the normal probability plot of residuals to determine whether the residuals satisfy the assumption of normality.

Time series regression models can be prone to producing residuals that are autocorrelated, which violates the assumption of independence of residuals. Serial correlation of error terms indicates inefficiency of OLS estimation and a probable bias in the estimation of sampling variances (Hansen and Narayanan 1981). It may also suggest the absence of a significant variable from the model (Billings and Jones 2008). Tests such as the Durbin–Watson can be used to assess serial correlation. Durbin–Watson results vary from 0 to 4, with results in the range 1.7 to 2.3 indicating minimal autocorrelation (Weber 1989). Billings and Jones (2008) suggest that serial correlation can sometimes be overcome by the addition of a suitable explanatory variable. Alternatively, an autoregressive term could be introduced to the model. Where this does not produce a satisfactory result, the Cochrane–Orcutt estimation procedure can be used to adjust the model for serial correlation of residuals.

The seasonality of water demand is one of the main causes of autocorrelated residuals. When the explanatory variables of the model do not sufficiently explain the seasonal variation in demand, this causes the autocorrelation to be passed on to the residuals. As mentioned above, autocorrelation of model residuals is often a symptom of an inadequately specified model, so the first step when attempting to address this problem should be to revisit the seasonal explanatory variables and identify missing variables. If it has not already been performed, seasonal adjustment of the model may provide a solution. Other options include:

- including an autoregressive or 'lag' term (demand at the previous time step) as an explanatory variable (Moglia et al. 2009, Weber 1993)
- using first differences of the response and (selected) explanatory variables in place of actual values in the model (Billings and Jones 2008); a formalised application of this is the Cochrane and Orcutt (1949) iterative procedure.

Multicollinearity in a multiple regression model occurs when two or more explanatory variables are highly correlated with one another. Perfect multicollinearity occurs when two independent variables have a correlation of 1 or –1, or when 'the sum of several variables is exactly equal to another variable' (Billings and Jones 2008). Perfect multicollinearity must be avoided because it makes it impossible to calculate the regression model. High multicollinearity should also be avoided, as it may decrease the precision of the associated regression coefficients, making it difficult to compare the relative significance of explanatory variables (Hansen and Narayanan 1981). The concept of parsimony also suggests that only one of a set of highly correlated variables should be included in a regression model. However, this may result in the inclusion of a less relevant explanatory variable over a more relevant one, particularly if they are secondary variables. Principal component analysis may also be used to overcome problems associated with multicollinearity. However, it generally makes the interpretation of the final model more difficult. The simplest way to check for the presence of multicollinearity in a dataset is to view a correlation matrix. There are also statistical tests, such as the variance inflation factor, that can be used to detect multicollinearity in a model. However, it can also be indicated by unstable regression coefficients and a high R value accompanied by low t-statistics (Hansen and Narayanan 1981).

3B.8 Model testing and inference

A number of methods may be used to determine the validity of a multiple regression model, such as the overall F-test, the coefficient of determination (R^2) and the adjusted R^2. The adjusted R^2 is generally preferable to the R^2, since it takes into account the degrees of freedom. The relative significance of each explanatory variable used in a regression model may also be evaluated using the change in R^2 or adjusted R^2 after the addition of an explanatory variable. However, this method tends to measure the amount of 'new' variation in the response variable explained by the additional explanatory variable. In this manner, the modeller may determine when to cease entering variables into a model. However, this method does not quantify the 'total' variation in the response variable explained by the additional variable, making it difficult to compare the relative significance of variables exhibiting high multicollinearity. Other statistical outputs used to determine the relative significance of explanatory variables include p-values, standardised regression coefficients and the confidence intervals associated with regression coefficients. In general, explanatory variables with lower p-values, standardised beta coefficients with larger absolute values, and regression coefficient confidence intervals not bounding zero are deemed more significant. Confidence intervals and predictions intervals may also be generated for a particular model, with smaller intervals implying better fits.

As with any modelling exercise, limited dataset sizes combined with large numbers of potential explanatory variables can lead to the problem of data overfitting. For this reason, it may be desirable to validate a constructed model using data not used for calibration, in what is known as an ex-post forecast. Models with poor predictive performance on the validation dataset are potentially deemed to be overfitted. The predictive performance may be evaluated using any number of statistics, such as the mean square error, Theil's U statistic and the average absolute error (Hansen and Narayanan 1981). Hansen and Narayanan (1981) also devised a method to test for regression coefficient instability related to multicollinearity using a reduction in dataset size. A total of 12 observations were removed from the dataset and the model was recalibrated. The unchanged regression coefficients were considered to suggest that they were stable.

4. Incorporating climate change into urban water IRP

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Summary

What is the purpose this paper?

The purpose of this paper is to provide urban water supply–demand planners with background information on the implications of climate change for urban water supplies and water demand. The aim is to inform decisions about how water utilities might manage risks posed by climate change. To do this, the paper provides information on:

- existing climate change projections and current knowledge of expected climate change impacts in Australia
- the risks posed by climate change to urban water supplies and water demand
- the points in an urban water supply–demand planning process where climate change needs to be considered and incorporated
- current thinking on developing climate change scenarios and incorporating them into supply–demand planning
- the changes in approach and types of available responses that can manage uncertainty about future climate.

The paper seeks to scope out the problem of climate change from an urban water supply–demand planning perspective and introduce potential approaches and methods that might be useful when incorporating climate change into urban water supply–demand planning in Australia.

From the perspective of an urban water planner, current knowledge about climate change leaves significant areas of uncertainty. The models available for projecting climate change commonly produce a wide range of potential future climates. The Australian climate is noted for its marked climate variability, and how human-induced global warming will interact with natural variability remains unclear.

This paper does not provide a step-by-step ‘how to’ guide for urban water planners, but background information on climate change impacts and risks as well as a consideration of the issues. In addition, the paper discusses available approaches for intergrating climate change into integrated resource planning (IRP) at each step of the IRP framework.

Why is the paper needed?

Climate is a major factor in determining available water supply for most towns and cities in Australia, and also influences urban water demand. Human-induced climate change is projected to increase global average temperatures and alter critical climate variables, including rainfall and evaporation, over the coming decades. Extreme events, such as floods and drought, are projected to increase in some regions. Human-induced climate change will also interact with natural climate variability.

In many locations, climate change has the potential to dramatically reduce supplies available from traditional water sources in coming decades. However, there is significant uncertainty about future climate, and some regions may see increasing levels of available supply. In

general, in the face of climate uncertainty, supply–demand planning will need to become more adaptive while also working towards reducing the vulnerability of urban water systems to climate change.

Because of the risks posed, dealing with the implications of climate change for urban water systems has become a central concern for urban water supply–demand planning. The risks to water utilities and communities from climate change include direct risks to water supply, such as reduced yields from surface water storages, increased customer demand and more frequent water restrictions. They also include financial and institutional risks, such as overinvestment in large supply augmentations and lack of certainty in water licences. Further risks are associated with community perceptions and expectations in relation to providing a reliable water supply and not increasing the greenhouse gas (GHG) intensity of water services.

Will this paper be useful to me?

The intended audience for this paper is urban water planners who are involved in developing supply–demand plans for cities or towns in Australia. However, it should also inform a wider audience that is interested in how urban water planning can be undertaken in the face of climate change. The paper has assumed a readership that is not completely new to this area and will have some knowledge of urban water issues. While the paper takes the IRP framework as its context, it is intended to act as a resource more generally for incorporating climate change into supply–demand planning.

How does climate change alter the planning and scoping steps in supply–demand planning?

The initial steps in any supply–demand planning process will include developing a picture of the supply–demand balance and establishing what the significant issues for the given region are. These are the planning and scoping steps of the process. The significant issues identified may include challenges, such as population growth or unsustainable use of groundwaters, but in many regions supply–demand planning is increasingly charactoristed by climate change and uncertainty about future climate.

Meeting the challenges that climate change poses will mean altering the analysis of supply–demand balance, changing supply–demand planning objectives, and reconsidering the process of supply–demand planning.

Analytically, best estimates of climate change should be incorporated into projections of long-term available supply and into demand forecasts (that is, yield estimates from rainfall-dependent supply sources and demand estimates for climate-dependent water demands, particularly irrigation and cooling). Uncertainties about future climate can be represented by high and low cases, representing wet and dry extremes.

Various methods that generate climate change scenarios for assessing urban water supply–demand planning are available. In Australia, the most widely accepted approach is to base climate change scenarios on global climate model (GCM) simulations and then to 'downscale' the simulations to a regional level by various means. In the absence of GCM-generated climate data, hypothetical and analogue climate change scenarios may be used to examine the sensitivity and relative hydrological impact of changes in climate.

This paper argues that an objective incorporating the implications of climate change into supply–demand planning needs to be added to other planning objectives. Furthermore, the paper argues that this objective has at least two component objectives:

- adaptation of urban water systems to the expected impacts of climate change and associated climate uncertainty
- mitigating the impacts of climate change through reducing the GHG emissions associated with the provision of urban water services.

However, supply–demand planners need to be cognisant of the various perspectives that can be brought to the question of planning for urban water in the face of climate change. For example, to manage uncertainty about future climate, strategies can be aimed at either decreasing the vulnerability of urban water systems to climate change (a climate change–resistant strategy, such as increasing the buffer between available supply and project demand) or by both decreasing vulnerability and increasing adaptive capacity (a strategy of climate change resilience, such as developing readiness options, the diversity of sources, or both).

Even in regions where water planning is conducted with a strong climate change–resistant stance, the uncertainties associated with climate change mean that planning is likely to become more adaptive. This will see (to at least some extent) a reconsideration of supply–demand planning processes. For example, an adaptive planning approach aims to be flexible so that it can respond to a range of possible futures, and is also responsive in that new information is sourced and fed back into future responses. An adaptive planning approach would also incorporate incremental responses to emerging uncertainties. This avoids the risks of making infrastructure investments now in anticipation of future climate scenarios that may not emerge.

In some regions in the future, climate change may result in a deeper reconsidering of supply–demand planning processes and deliberate policies that accommodate supply augmentations and demand-management programs triggered by drought events rather than projected growth in demand. However, without defined governance and public engagement in demand–supply planning, any moves towards more adaptive approaches for urban water are unlikely to be effective.

What responses are available?

In many industries, the first step in managing climate change will be to look at the mitigation of GHG emissions. In urban water, however, adapting to climate change will also be crucial. Important elements of a response to climate change and climate uncertainty include a diversity of water supply and conservation options, the development of contingency measures, and adaptive management, including ongoing monitoring.

Accounting for emissions

GHG emissions from water supply are generated directly via surface emissions from water storage reservoirs and indirectly from the use of energy from non-renewable carbon-based sources. Energy is used in treating water to a potable standard and in pumping to deliver the water. Energy is also used by customers for heating water, which accounts for approximately one quarter of all residential energy consumption in Australia. Wastewater treatment also generates direct and indirect releases of GHGs due to energy use. Compared to overall energy-related emissions, emissions from the urban water industry as a whole are currently a small but rapidly growing contributor to Australia’s total.

Developing more climate change resistant or resilient portfolio

Responding to climate change will mean developing more climate change resistant or resilient portfolios of options. The full extent of this in practice, and how to assess it, are likely to remain contested for some time. This paper outlines two key elements that will certainly be core to climate change responses around the country: increasing portfolio diversity and developing adaptive measures.

A greater role for monitoring, evaluation and review

In general, there will be an increasing role for monitoring and evaluation in the face of climate change. This is both a mechanism to measure the effectiveness of the implemented responses and to manage uncertainties associated with climate change.

Where to look in the paper?

Some parts of the paper might be of interest to particular reader groups:

- Section 4.2.1 covers the projected impacts of climate change across Australia and the interaction of climate change with natural climate variability.
- Section 4.2.3 summaries some of the risks posed to urban water supply by climate change.
- Section 4.3.1 discusses how climate change will affect planning objectives for urban water.
- Section 4.3.2 describes moves towards more adaptive planning, and the role of adaptive management and adaptive measures.
- Section 4.4.1 details methods for generating climate change scenarios.
- Section 4.4.2 outlines considerations for selecting climate change scenarios.
- Section 4.5.1 addresses accounting for GHG emissions and mitigation.
- Sections 4.5.2 and 4.5.3, respectively, cover the development of diverse portfolios and adaptive measures, such as readiness options.

What are the take-home messages?

The core messages that should be taken from this paper are as follows:

1. Accounting for the implications of climate change should be an integral part of urban water supply–demand planning.
2. The mitigation of GHGs needs to be a parallel objective to climate change adaptation in urban water supply–demand planning.
3. Demand-management programs that increase water-use efficiency help to meet both climate change mitigation and adaptation objectives.
4. The 'best estimate' of expected climate change should be included in calculations of the longer term supply–demand balance, as well as in yield estimates for new climate-dependent options.
5. Uncertainty about future climate due to climate change can be managed. This can occur either via a strategy aimed at decreasing vulnerability to climate change or by both decreasing the vulnerability and increasing the adaptive capacity of the urban water system.
6. Important questions remain about how best to manage climate uncertainty, including 'How are we to to differentiate climate change from natural climate variability?', 'What represents a "reasonable" worst case climate change scenario?' and 'How can we assess whether a portfolio of options is the most cost-effective and sustainable means of providing resistance, resilience or both to climate change?'

4.1 Introduction

Climate is a major factor in determining available water supply for most towns and cities in Australia, and also influences water demand. Human-induced climate change is projected to increase average global temperatures and alter both rainfall and evaporation in the coming decades. In addition, climate extremes are expected to increase, with more severe droughts and floods. This comes on top of natural variability in inter-annual and longer term climate patterns in Australia. Urban water systems are vulnerable to changes in climate, and concern about climate change has already influenced major decisions in the urban water sector in Australia. What the risks are for the sector and how best to manage them remain topics of ongoing discussion.

The interaction of climate change and urban water planning is a wide and emerging topic area. It spans the linkages between climate science and hydrology, hydrology and urban water supply, climate and water demand, and aspects of the water–energy nexus. It draws on systems concepts such as 'resistance', 'resilience' and 'adaptive capacity' in relation to water systems and 'complexity' and 'step change' in relation to the climate system. Information about climate change impacts in Australia, particularly at the regional level, leaves significant uncertainty about the expected extent and timing of potential impacts. That uncertainty is a particular challenge for urban water planning. For urban water planners, climate change therefore creates a complicated picture that this paper seeks to clarify, based on the current state of knowledge in the field.

Taking the existing Australian IRP framework (Turner et al. 2008) as its context, this paper scopes the major risks that climate change poses for urban water supplies and demand, and the implications for supply–demand planning. It aims to provide an introduction and background to the approaches and methods that could be used in managing urban water systems in the face of climate change in Australia. The paper addresses the issues and available approaches at each step of the IRP framework.

4.1.1 Outline of this paper

Apart from this introductory section, this resource paper has six main sections:

- Section 4.2 provides background and answers three questions: what are the potential impacts of climate change in Australia? what risks are posed to urban water supplies by climate change? how have Australian water utilities responded to climate change?
- Section 4.3 addresses Step 1 of the IRP framework, which covers planning the overall process. This includes the consideration of planning objectives for an urban water system. For many regions, assuring the supply of water to urban areas in the face of climate change will be the foremost objective. However, alongside this 'adaptation' objective there must also be an objective of mitigating the GHG emissions that result from water service provision. These mitigation and adaptation objectives have implications across the IRP process. This section also discusses how dealing with the uncertainties associated with climate change requires more adaptive approaches to planning.
- Section 4.4 focuses on Step 2 of the IRP framework, which involves analysing the existing water supply and demand situation in a given region. It covers methods for developing regional climate change scenarios and the application of those scenarios in estimates of available supply and forecast demand. It also addresses the selection of scenarios that can represent a 'worst case' for testing supply–demand plans.
- Section 4.5 focuses on Step 3 of the IRP framework ('Develop the response'). This step includes designing individual supply- and demand-side options, assessing options against each other, and developing a suite or portfolio of options that will secure water supplies into the future. The first issue addressed by this section is accounting for the GHG emissions in order to manage and mitigate the GHG impact of any response. The two further areas discussed are the development of diversity in the portfolio of options and approaches for managing climate uncertainty.
- Section 4.6 considers how climate change and climate uncertainty increase both the range of parameters that water utilities and water planners need to monitor and evaluate and the frequency of review. This aligns with Step 5 of the IRP framework.
- Section 4.7 draws conclusions from the paper and sets out key considerations for prospective water planners dealing with the question of climate change.

A collection of further resources that are relevant to the topics covered in the paper is included in Section 4.8.

4.1.2 Scope of this paper

The purpose of this paper is to provide background information for the Australian water industry on approaches to incorporating the potential impact of climate change into urban water supply–demand planning. As climate change is an evolving area of science, this paper does not aim to prescribe particular methods but instead aims to canvass useful approaches. As far as the authors are aware, there is no common understanding of the uncertainties in climate change projections and how those uncertainties should be incorporated into urban water supply–demand planning across Australia. The paper's goal is to provide sufficient information to map out that space, based on current knowledge.

The intended audience for this paper is urban water supply–demand planners working at the scale of a single utility's area of operations or planning for a particular water system, although it will also interest others in the urban water and water policy fields. It is assumed that readers are not completely new to this area and will have some knowledge of urban water planning. While the paper takes the IRP framework as its context, it is intended more generally to be a resource for incorporating climate change into urban water supply–demand planning.

This resource paper should be read in conjunction with other resources that relate to aspects of urban water supply–demand planning and climate change, including Water Services Association of Australia (WSAA) occasional papers and National Water Commission (NWC) publications. Some state government departments have already compiled, or are currently compiling, guidelines for incorporating climate change into urban water supply–demand planning. Those guidelines should be sought out and adhered to as required. The guidelines and other resources are listed in Section 4.8.

4.2 Background

4.2.1 What are the potential impacts of climate change in Australia?

Projected impacts of climate change across Australia

In its fourth assessment report, the Intergovernmental Panel on Climate Change (IPCC) presented a substantial body of research that supports a picture of a warming world and significant changes to regional climates across the globe (IPCC 2007). The report also states that further global warming and regional climate change can be expected because of projected increases in GHG concentrations in the atmosphere. The projected increases vary, based on different assumptions about human activity, including assumptions about the demographic, economic and technological factors that will influence future emissions. The IPCC has therefore developed and analysed a range of potential emissions scenarios for this century (IPCC 2000), which form the basis for developing global projections of human-induced climate change.

The development of regional climate change projections in Australia is facilitated by the use of global climate model (GCM) simulations. In the absence of regional climate modelling studies, GCMs are the most credible tools for estimating the response of regional climates to enhanced GHG (and aerosol) emissions. In 2007, the Commonwealth Scientific and Industrial Research Organisation (CSIRO) and the Bureau of Meteorology (BoM) used 23 GCMs to project the impacts of climate change in Australia; the results of those simulations are presented in CSIRO and BoM (2007a). Overall, climate change projections were found to vary between regions and with different emissions scenarios. On average, the 50th percentile estimate of annual warming over Australia by 2030 (relative to 1990) was about 1°C for mid-range emissions scenarios. This varied between a little less in coastal areas and a little more inland. Unlike temperature, the rainfall projection decreases or increases depending on location (CSIRO and BoM 2007a). Over the period to 2030, the average annual rainfall is projected to decrease in southern regions but will vary in other regions. In some parts of Australia, regional climate change studies projected slight increases in rainfall and runoff—a regional study of the Hunter region in New South Wales being one example (Blackmore and Goodwin 2009). Annual potential evapotranspiration is projected to increase across the country, with the largest increases in the north and east.

Human-induced climate change is projected to have impacts not only on the mean climate but also on climate extremes, such as droughts and extreme precipitation. Drought occurrence is projected to increase in the south of Western Australia and eastern Australia and remain relatively unchanged in other regions, such as north-west and north Queensland (CSIRO and BoM 2007b, Hennessy et al. 2008, Kirono et al. 2009). Extreme daily precipitation (highest 1%) is projected to increase in the north, with widespread increases projected in summer and autumn. In the south, however, such extreme daily rainfall events are projected to decrease, particularly in winter and spring when there is a strong decrease in mean precipitation (CSIRO and BoM 2007b).

Changes in either climate averages or climate extremes can have substantial implications for water supply in Australia's cities and towns. However, the impacts of climate change on rainfall and evaporation will vary across regions, so the impact on urban water systems will be different depending on location. Box 4.1 illustrates some of the broad regional differences in rainfall changes projected for Australian regions and selected cities.

Box 4.1: Examples of regional differences in projected climate change impacts

Some of the projected regional impacts of climate change on rainfall are:

- Queensland east coast: possible drying trend (CSIRO and BoM 2007a)
- New South Wales coast: no change to slight reduction in eastern parts of the state (DWE 2008); slight increases in some mid-north coast regions (Blackmore and Goodwin 2009)
- Murray–Darling Basin: surface water availability likely to decline, particularly in the south of the basin (Chiew et al. 2008)
- southern Victoria: decline in rainfall, particularly in winter and spring (CSIRO and BoM 2007a)
- south-west Western Australia: decline in rainfall, particularly in winter and spring (CSIRO and BoM 2007a)
- tropical Australia: changes in rainfall pattern are unclear (CSIRO and BoM 2007a

Projected rainfall changes for selected Australian cities

Results in the table below are indicative, in that they are based on the results of coarse-grid GCM for the locations and do not take into account local topographical effects (CSIRO and BoM 2007a). A1B, B1 and A1F1 are emissions scenarios, while 10p, 50p, and 90p represent a range of projections from multimodel simulation (the 5th, median and 90th percentiles, respectively).

	Season	2030 A1B 10p	2030 A1B 50p	2030 A1B 90p	2070 B1 10p	2070 B1 50p	2070 B1 90p	2070 A1FI 10p	2070 A1FI 50p	2070 A1FI 90p
Adelaide	Annual	-11	-4	+2	-18	-7	+4	-32	-13	+8
	Summer	-14	-2	+11	-23	-3	+18	-39	-5	+35
	Autumn	-11	-1	+9	-18	-2	+14	-31	-4	+28
	Winter	-15	-6	+2	-23	-10	+3	-40	-19	+6
	Spring	-19	-8	+3	-30	-12	+4	-50	-23	+8
Brisbane	Annual	-12	-3	+5	-18	-5	+9	-33	-9	+17
	Summer	-11	-1	+9	-17	-1	+15	-31	-3	+29
	Autumn	-14	-3	+10	-23	-5	+16	-39	-9	+31
	Winter	-15	-6	+4	-24	-10	+6	-42	-18	+11
	Spring	-17	-6	+6	-28	-10	+10	-47	-18	+18
Canberra	Annual	-9	-3	+2	-14	-5	+4	-26	-9	+8
	Summer	-8	0	+8	-12	0	+13	-22	+1	+25
	Autumn	-10	-2	+6	-16	-3	+10	-29	-6	+20
	Winter	-14	-5	+3	-22	-9	+5	-38	-16	+10
	Spring	-17	-6	+3	-27	-10	+5	-46	-19	+10
Darwin	Annual	-7	-0	+6	-11	-1	+10	-21	-1	+20
	Summer	-6	0	+7	-10	0	+11	-18	+1	+21
	Autumn	-11	0	+11	-18	0	+18	-32	0	+34
	Winter	-27	-4	+18	-41	-7	+31	-63	-13	+59
	Spring	-21	-5	+13	-33	-8	+22	-54	-15	+42
Melbourne	Annual	-9	-4	+1	-14	-6	+1	-25	-11	+3
	Summer	-11	-1	+9	-17	-2	+14	-30	-4	+27
	Autumn	-9	-2	+6	-14	-2	+10	-25	-5	+19
	Winter	-10	-4	+2	-17	-7	+3	-30	-12	+5
	Spring	-16	-7	+1	-25	-11	+1	-43	-21	+2

Uncertainties in estimating climate change impacts for urban water

Despite the work done to date on projecting climate change impacts, a number of uncertainties remain, including in relation to:

- the future atmospheric GHG concentrations (emissions trajectories)

- how much the global average surface temperature will respond to increases in atmospheric GHG concentrations
- how changes to the climate as a result of global warming will vary spatially, and hence how the climate of the region under consideration will respond to an increase in global surface temperature.

The uncertainty is lower in regions where regional climate studies have occurred and where the projections from a range of GCMs are seen to converge. Multiple studies taking various approaches now exist for some Australian regions, giving increased confidence when the predicted impacts align.

However, in general there is greater certainty about projected changes in temperature than about changes in rainfall. Additionally, for water planning the interactions of climatic and hydrologic variables depend on the local characteristics, such as soil type, vegetation and groundwater storage, which are unique to particular catchments. The rainfall–runoff issue therefore adds a further layer of uncertainty to estimating available water supplies under climate change.

Significantly, the phenomenon known as 'catchment drying' means that the decrease in runoff commonly exceeds the decrease in rainfall. This is due to increased evapotranspiration, which creates a greater soil moisture deficit that must then be satisfied before runoff is generated. One rule of thumb that has been suggested is that the rainfall elasticity of runoff is about 2 to 3.5 (Chiew 2006, Jones et al. 2006). This would mean that a 10% change in mean annual rainfall would lead to a 20%–35% change in mean annual runoff. A more robust approach is to use an appropriate hydrological model to estimate the impacts of climate change on runoff in a specific catchment. There are many different hydrological models; those commonly used in Australia are available from the Rainfall–Runoff Library (Podger 2004). Some differences in catchment runoff estimates can generally be expected when different hydrological models are used. This is due to the models' use of different approaches to transform rainfall into runoff. However, the impact on runoff of various local catchment characteristics is likely to be small compared to the range of runoff results that can be attributed to climate change projections from the different GCMs (Chiew et al. 2009). More discussion of climate change scenarios for use in supply and demand assessment is provided in Section 4.3.2.

Natural climate variability and climate change

In many regions, water planners are looking to differentiate the impact of climate change from the affects of an ongoing drought or extended dry period. However, that task is far from trivial due to natural climate variability in many regions of Australia.

The Earth's climate is a complex system and is variable on a range of timescales. Variability obviously exists between seasons but is also inter-annual. Climate patterns also create decadal and multidecadal variability, and longer term variability also occurs. That variability is natural, in that it is not a result of human activity.

The Australian climate is noted for its variability, and the inter-annual and decadal variability of Australian rainfall has been linked to several broadscale climate patterns. The El Niño – Southern Oscillation (ENSO) is a dominant driver affecting Australian inter-annual climate variability. At a decadal scale, the Australian climate also shifts between modes, including the oscillating El Niño – La Niña dominated phases of ENSO. This is influenced by the Interdecadal Pacific Oscillation (IPO), which lasts roughly 22 years. There are also oscillating modes of drought and flood-dominated periods that affect mean rainfall and rainfall intensity over several decades or more (Jones 2006).

Changes between these different modes can be relatively abrupt. Significant changes from drought- to flood-dominated modes have been detected in Australian rainfall records in eastern Australia in 1946–48 and 1972 and from flood- to drought-dominated modes in eastern Australia in 1895 and south-west Western Australia in 1946 and 1965–67 (Vivès and Jones 2005, Li et al. 2005). Such changes in mode might be seen as a structural shift in the climate, as a number of key climatic and hydrological parameters will change together for a period. In water planning, such a shift would be seen as a sudden rather than gradual change in climate variables, particularly rainfall and runoff.

The complex nature of the climate system means that human-induced climate change might force or exacerbate structural shifts in climate. In some regions of Australia, observed decreases in runoff in recent years and decades have now been interpreted by planning authorities as 'step changes'; some planning authorities have attributed the step changes to climate change.

Perhaps the most well-known example in Australia is Perth, which experienced an eight-year sequence (1997–2004) of inflows to storages that was on average approximately 30% lower than the post-1974 average (Water Corporation 2005), which was approximately 50% lower than inflows over the entire historical record. This has been interpreted by water planning authorities as a step change in stream flows for water supply–demand planning in Perth. As a result, Western Australia's Water Corporation now applies the last 20 years of inflows as the baseline for projections to 2030.

Another, more recent example is Melbourne, where inflows to storages appear to have dropped significantly over the past decade: average inflows from 1997 to 2006 dropped by approximately 35%, and inflows in 2006 were the lowest on record. This trend has also been treated as a step change in inflows by water planners in Melbourne (DSE 2007). Decision making in Melbourne Water will therefore use the last 12 years of inflow data (Moran 2008).

A level of uncertainty remains as to whether these observed 'step changes' in runoff are the result of human-induced climate change or are the impact of modal shifts. Even though they lie outside the historical record being used for urban water supply planning, there is speculation that they may be within the range of natural variability. For example, CSIRO has recently undertaken a study to characterise climate in south-east Queensland. The outcomes of the study so far indicate that the observed changes to climate in that region lie within natural variability (Cai et al. 2010).

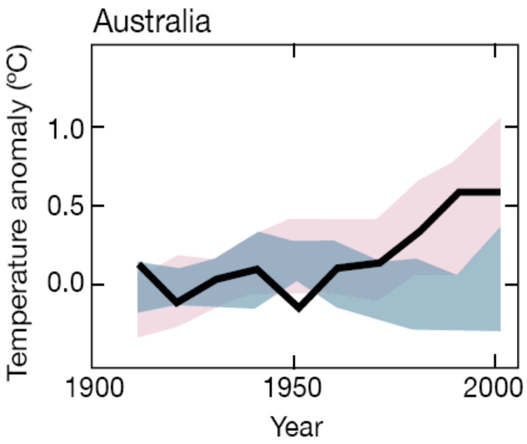
Separating human-induced climate change impacts from natural climate variability is not a trivial task. Existing attribution studies suggest that warming in Australia since the middle of the 20th century is likely to be mostly due to anthropogenic increases in GHG (CSIRO and BoM 2007b) (see Box 4.2). However, some recent studies have seen the drying observed in south-west Western Australia and south-east Queensland, for example, as the result of natural fluctuations in the climate (Ryan and Hope 2005 Cai et al. 2010). But, for others, increasing GHG concentrations are contributing to the observed rainfall decline (Timbal et al. 2006).

Significantly, while work is underway to improve the next generation of climate projections so they integrate natural decadal variability with climate change projections (Watterson and Whetton 2008, 2010), current projections for Australia do not include natural variability. In time, the management of water resources will require a 'whole-of-climate' approach that integrates natural climate variability with climate change projections. One approach to incorporate climate variability (described in Section 4.3.2) is to include climate trends or different climatic modes as different baseline climate or hydrological data when estimating supply availability.

Box 4.2: Is observed climate change in Australia due to GHG emissions?

The figure below is a comparison of Australia-wide observed continental-scale changes in surface temperature. The results were simulated by climate models using climate 'forcing' due to natural factors only and using forcing due to natural factors plus human-induced GHG emissions. The figure shows observed Australia-wide changes in surface temperature (black line, decadal averages), with results simulated by climate models using only natural forcing (darker shaded band) and natural plus anthropogenic (human-induced) forcing (lighter shaded band). Changes are relative to the average for 1901–1950. Both the shaded bands show the 5%–95% range of values evident across GCM simulations.

Observed and modelled surface temperature



Source: IPCC (2007).

In summary, the figure suggests that the observed increase in temperature cannot be explained by natural forcing alone.

4.2.2 What risks are posed to urban water supply by climate change?

A number of types of risk are evident in any consideration of how climate change might affect water service providers and water supply to a community. As well as the direct risks to urban supply, there will be financial and institutional risks and risks associated with community perceptions or expectations. Some examples of such risks are set out in Table 4.1.

Formally, risk is characterised by a consequence or hazard with an attached likelihood. As used in this paper, however, 'risks' refer specifically to possible adverse outcomes or consequences to water supplies due to climate change. This is an acknowledgment that uncertainty about climate change projections in many regions means that we are not able to reasonably estimate the probability of low probability (by high impact) events in many instances. However, that is not true for all risks. For example, a reasonable estimate of the likelihood that a water utility will not be able to maintain expected 'level of service'[1] obligations with its existing supplies may well be possible by including the climate change projections for the region in both supply and demand forecasts.

[1] The 'level of service' describes the frequency, duration and severity of water restrictions that can be expected from a given supply system over the long term (Erlanger and Neal 2005).

Table 4.1: Examples of the risks posed by climate change to urban water supplies

Risk	*How the water utility or community would be affected*
Direct supply system risks	
Reduced yields from surface water storages or river-drawn supply systems.	Emergence of supply–demand tensions, resulting in water utility not meeting its level of service obligations.
Increased variability in rainfall increases the frequency of water restrictions.	
Increased total or seasonal demand (e.g. outdoor water use, evaporative cooling).	
Damage to coastal groundwater supply from seawater intrusion caused by rising sea levels.	Partial or total failure of that supply source.
Failure of a particular surface water source due to prolonged low or no inflows.	
Decreased groundwater availability due to reduced recharge.	
Damage to assets (including distribution pipelines and other assets).	Ground movement due to soil moisture changes and soil drying may damage pipelines.
	Lower flows and warmer temperatures may increase the corrosion of pipelines.
	Sea-level rise may inundate low-lying assets.
Increased incidence of bushfires.	Increased fire activity has the potential to damage water catchments, affecting both water quality and quantity. Ash and sediment may contaminate supplies, while vegetation regrowth after fire will decrease yields.
Reduced water quality resulting from more frequent algal blooms and increased sediment loads.	The frequency of algal blooms could increase due to a combination of low flows, elevated temperatures and higher contaminant loads. Soil erosion in catchments could increase from more intense rainfall events.
Institutional and financial risks	
Overinvestment in supply-side resulting from planning augmentation to meet the 'worst case' scenario.	Significantly increased cost of water services.
Reduced access conditions on water licences in response to reduced inflow to river systems.	Partial loss of previously available supply.
Increased competition for water resources.	Increased cost for water or partial loss of previously available supply.
Increased pipe breaks due to soil moisture change (damage to distribution assets).	An increase in non-revenue water loss.
Decreased revenue due to increased water restrictions.	Financial pressure on water utility.
Energy price increases under a Carbon Pollution Reduction Scheme or similar carbon pricing policies.	Exposure to higher energy prices as a result of carbon emissions costs being passed through to water utilities in energy tariffs.
Community perception and expectation risks	
Community expectation that the level of service of water supply should be maintained regardless of drought.	Some customers will perceive ongoing water restrictions under extended drought periods as a failure by the water utility.
Community expectation that drought restrictions should be maintained regardless of storage levels.	When restrictions are eased, there is a risk that the community will perceive that the water service provider is not taking climate change seriously enough, although storages have risen above a predefined trigger level.
Loss of trust in water utility's ability to provide a continuing water service.	Net movement of people or industry from areas of perceived or actual water shortages.

Risk	*How the water utility or community would be affected*
Low inflows may impair the water utility's ability to maintain the recreational and environmental benefits from water storages.	Low water levels in reservoirs result in decreased environmental and recreation values of water storages to the community.
Community perception that water utility has overreacted to climate change uncertainties, causing unnecessary costs for customers and damage to the environment.	Community distress at significantly increased cost of water services. Loss of trust in water utility as a responsible environmental manager.
Expectation that water utility must mitigate all GHG impacts of proposed supplies.	Community expectation means that water utility will need to ensure that a new source is 'carbon neutral' in order not to make the climate change problem worse.
Perception that the water utility should be aiming to act sustainably in all its operations in the face of climate change.	Community expectation that water utilities will act responsibly with regard to sustainability. This is complicated by the interconnections between water, energy and climate change issues.

4.2.3 How have Australian utilities responded to climate change?

In the mitigation of GHG emissions and adaptation to a changing climate, Australian water utilities have been at the forefront of the nation's response to climate change. Examples of mitigation and adaptation responses by utilities are described in this section.

Mitigation responses

Over the past decade and especially in the last few years, water utilities have been active in efforts to mitigate GHG emissions. Some utilities, such as Sydney Water Corporation and the water utilities in Melbourne, have announced plans to move towards carbon neutrality over the coming 10–15 years, and many others are also planning to make large GHG reductions over that period.

Many utilities have pursued energy efficiency in their operations, developed processes to capture and utilise biogas from wastewater treatment, and worked to reduce fugitive emissions from wastewater treatment plants. More recently, some water utilities have purchased Green power or are building renewable energy generation capacity in order to power new energy-intensive supply infrastructure. Other utilities are looking at reforestation and purchasing carbon offsets. Some are considering the impact they can have through demand-management programs that reduce their customers' demand for hot water and therefore energy for water heating.

Adaptation responses

Drought restrictions have long been the major adaptive response of water utilities to handle Australia's variable climate. Despite the effectiveness of restrictions in managing climate-related risks in the past, the perceived additional risks posed by climate change have already prompted large-scale investment in new water sources by many of the largest water utilities in the country. Five of Australia's largest cities (Sydney, Melbourne, the Gold Coast, Perth and Adelaide) have built or are building desalination facilities. Other significant supply-side responses being undertaken in Australia include the construction of an intercatchment transfer pipeline for Melbourne, large-scale wastewater reuse schemes in Brisbane and Sydney, and plans for major dam upgrades and construction to supply Canberra. As well as these large-scale supply-side augmentations, many smaller scale stormwater and wastewater reuse projects have been initiated in urban areas across the country. Planned expenditure on new urban water infrastructure in Australia will total $30 billion over the next 5–10 years (WSAA 2008).

This investment in new water sources has already been accompanied by a rise in the energy intensity of urban water supplies in Australia. Kenway et al. (2008) showed that the energy intensity of water supplied in Adelaide and Perth doubled between 2001 and 2006, and quadrupled in Sydney over the same period. The energy intensity of water supply is set to rise further as new water infrastructure projects currently being completed come online.

Despite an apparent commonality in the response to climate change in Australian cities, indicated by the investment in new supplies, there are differences in supply–demand approaches. In 2007, a review by an independent working group of the Prime Minister's Science, Engineering and Innovation Council found significant variation in the supply–demand planning approaches adopted by the cities that were reviewed (Brisbane, Sydney, Melbourne, Adelaide and Perth) (PMSEIC 2007). These included different strategies for dealing with climate uncertainty and 'sharply differing judgments about the acceptable degree of risk'. Variations were also noted in:

- reliance on or rejection of the past hundred years as the best indicator of future climate or inflows
- the extent to which and the way that climate change projections and regional climate change scenarios were incorporated into estimates of available supply and demand
- the levels of service that are considered to be acceptable to the community, and therefore the willingness to use drought restrictions as a mechanism to manage climate-related risks
- willingness to consider unconventional options, including decentralised supply options such as stormwater use and local recycling, indirect potable reuse etc.
- the degree of reliance on (and confidence in) demand-management programs to achieve reductions in per capita water consumption
- the degree of integration of 'other' large supplies, such as groundwater and interbasin transfers
- the extent to which explicit and specified 'readiness options' and drought 'contingency measures' were developed and would be triggered in the event of continued and/or extreme drought conditions. (See Section 4.5.3 for 'drought planning' and 'readiness options').

It is not surprising that there have been significant variations in Australian water utilities' responses to climate change, as the industry has been at the forefront of the nation's response to this challenge. The water industry should expect to stay at the forefront, because even small increases in temperatures translate to less runoff and increased water demand in some regions. Also, new sources of water, such as desalination plants, are far more energy-intensive than traditional supplies, and water utilities might expect the community to be concerned about the impact of rising energy use on the climate.

Being at the forefront of GHG mitigation and climate change adaptation responses is challenging and, as these examples show, the water industry is still learning how best to balance the twin objectives of adaptation and mitigation.

4.3 Planning the overall process

This section is the first of four that address how climate change will affect the IRP framework steps. This section addresses Step 1 ('Plan the overall process'). This step includes establishing the significant water planning issues for a region, which should translate into the planning objectives for the urban water system in question.[2]

This section first discusses objective setting and 'framing' the challenges posed by climate change, covering both mitigation and adaptation. It then discusses 'adaptive management' in more detail as a key approach in dealing with uncertainty about future climate. The section concludes by considering the points in the IRP process where climate change and climate uncertainty will need to be accounted for.

4.3.1 Setting objectives in the context of climate change

The primary objectives of supply–demand planning can generally be characterised as:

[2] Note that the specific planning objectives for an IRP study should also be reassessed once the supply–demand situation has been established in the final stage of Step 2.

1. Ensure that the community has a safe and reliable water supply
2. Provide water services cost-effectively
3. Account for sustainability impacts.

Each of these primary objectives has component objectives, which in turn might have subcomponents that are specific to the water planning situation in a given location.

For Erlanger and Neal (2005), the principal objective of ‘ensuring that the community has a safe and reliable water supply’ has components of ensuring:

- that the supply system has the capacity to meet demand in most periods
- that there is a drought response plan of implementing water restrictions to provide short-term protection against running out of water during a drought
- in the case of an extreme drought, that there is a contingency or emergency plan to ensure that the basic water needs of the community can be met.

From an IRP perspective, as detailed in Turner et al. (2010), ‘providing water services cost-effectively’ might be seen to involve:

- supply–demand planning based on a detailed demand forecast
- considering the full range of demand-side options alongside supply-side options
- assessing demand-side and supply-side options on an equal basis, in which conserved water is treated equivalently to new supply.

As with the objective of ‘accounting for sustainability impacts’, this will have economic, social, technical and environmental components. *Sustainability assessment in urban water integrated resource planning* (Fane et al. 2010, in this document) provides a detailed discussion on including sustainability into options assessment for urban water.

Climate change and uncertainty about future climate have a bearing across each of the above objectives. A further primary objective of any supply–demand planning exercise for urban water might therefore be framed as:

4. Incorporate the implications of climate change into urban water planning.

As discussed in this section, incorporating the implications of climate change will have at least two component objectives:

- mitigating the impacts of climate change by reducing the GHG emissions associated with the provision of urban water services
- adapting urban water systems to the expected impacts of climate change and associated climate uncertainty.

The mitigation objective

The objective of climate change mitigation may include sub-objectives such as:

- accounting for the GHG emissions of water demand- and supply-side options and conservation measures in decision making
- managing urban water in a manner that minimises the GHG intensity of water service provision
- moving water utility operations towards carbon neutrality.

GHG emissions from water supply are generated directly via surface emissions from water storage reservoirs and indirectly due to the use of energy from carbon-based sources in treating and delivering potable water (Hall et al. 2009). Energy is also used by customers for heating hot water, which accounts for approximately one quarter of all residential energy consumption in Australia (Retamal et al. 2009). Wastewater treatment also generates direct and indirect releases of GHG emissions.

In energy-related emissions alone, the urban water industry as a whole is currently a small but rapidly growing contributor to Australia’s total. The energy used by the major water utilities in Sydney, Melbourne, Perth, Brisbane, the Gold Coast and Adelaide has historically been approximately 0.2% of total urban energy use (Kenway et al. 2008). However, the objective of climate change mitigation needs to be viewed in the context of increasing GHG emissions as a result of the water industry in Australia. While urban water systems have not been major energy users in the past, several cities have more than doubled the energy intensity of their water supply systems in the past decade due to the incorporation of desalination plants and intercatchment transfers (Kenway et al. 2008). The energy intensity of water service provision is expected to increase further with new desalination plants, interbasin transfer pipelines and major recycling plants being planned or already under construction.

Therefore, there are strong reasons why the water industry should continue working towards not increasing and, where possible, reducing direct and indirect GHG emissions from water supply. In particular, water utilities will require a level of community endorsement of their responses to climate change, and this creates community expectations that utilities will play their part in reducing GHG emissions. Like the need for climate change adaptation, the mitigation imperative associated with managing urban water systems is becoming more critical over time.

The adaptation objective

Adaptation is defined by the IPCC as ‘adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities’ (IPCC 2007). The adaptation objective has impacts across the supply–demand planning process (see Section 4.3.2). However, different people and organisations will ‘frame’ the problem of climate change adaptation in urban water quite differently.

To illustrate the variation in perspectives, four that appear evident in discourse in Australia are characterised below and illustrated in Figure 4.1:

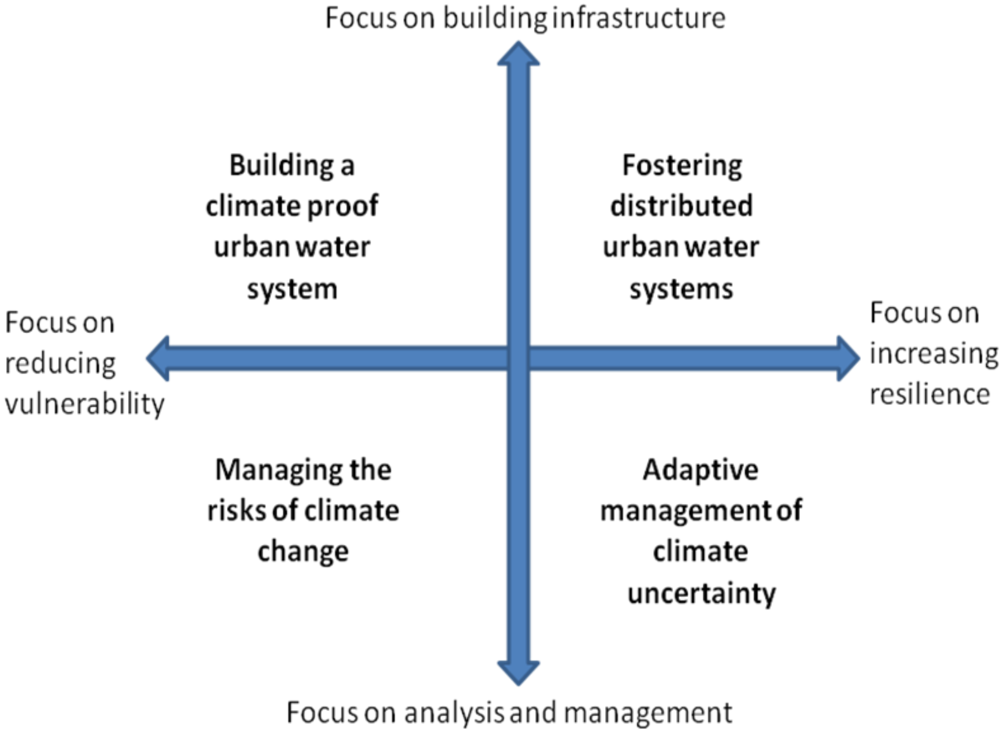
1. *Building a ‘climate-proof’ water system* is a perspective that seeks to remove the vulnerability of the urban water system to climate change by building new centralised supplies. This perspective is characterised by:
    - planning to create a high degree of certainty about water supplies through significant supply augmentation
    - looking to climate-independent sources of water supply
    - planning supply capacity so that there is a significant buffer above forecast demand
    - aiming to remove or greatly reduce the need for water restrictions
    - using ‘worst case’ climate change scenarios to determine the supply–demand balance.

From this perspective, the adaptation objective might be seen as ‘building a climate-proof or drought-proof water supply system for the region’.

2. *Fostering distributed water systems* is a perspective that aims to increase the resilience of urban water systems by developing myriad distributed water systems, such as rainwater tanks, stormwater harvesting, and onsite or in-building wastewater reuse. These would be located throughout the city. This perspective is characterised by:
    - a long-term perspective and a goal of transforming urban water systems
    - making use of available local sources of water supply as the solution
    - having many sources of water within the city
    - moving away from urban water supplied solely by centralised water utilities
    - developing a broader goal, beyond water supply, of creating a water sensitive city.

From this perspective, the adaptation objective might be seen as ‘encouraging and developing a diversity of sources of supply at various scales in conjunction with the existing centralised water systems in order to create a water sensitive city’.

Figure 4.1: Differing perspectives on climate change adaptation in urban water



3. *Managing the risks of climate change* is a perspective that aims to decrease the vulnerability in the portfolio of options through quantified risk management. It is characterised by:
   - an understanding of climate change in terms of a set of quantifiable risks with knowable likelihoods
   - applying a comprehensive risk-based planning and evaluation framework
   - incorporating risk analysis and risk management tools, such as financial portfolio theory and real options analysis
   - aiming to develop the optimal portfolio of options.

From this perspective, the adaptation objective might be seen as 'develop a risk-weighted portfolio that minimises the risks of climate change to our city's water supply system'.

4. *Adaptive management of climate uncertainty* is a perspective that increases the resilience of urban water systems through developing adaptive measures that can be deployed as the situation evolves. This perspective is characterised by:
   - an image of the future as being uncertain due to climate change
   - preplanning of potential supply- and demand-side readiness options
   - detailed analysis of storage drawdown curves and trigger points for the readiness options under various future climate scenarios
   - holding off decisions to build new supplies until absolutely necessary, and understanding when that is
   - having a readiness strategy in place and monitoring the emerging scenario.

From this perspective, the adaptation objective might be seen as 'developing options that will allow us to adapt in a severe drought and identify when we will need to trigger those options'.

It is important to recognise that the four perspectives are simplified here and that, in practice, they overlap. What is important for a water planner is awareness that different stakeholders will bring a range of perspectives to the question of climate change adaptation in urban water planning. Furthermore, it is useful to reflect on the fact that, if a single stance comes to dominate the planning process in a region, that will strongly influence the eventual outcomes and preclude consideration of the full range of options.

One distinction used throughout this paper is between the ‘climate change resistant’ and ‘climate change resilient’ stances to adaptation:

- A *climate change resistant stance* focuses on reducing the vulnerability of the urban water system to the impacts of climate change. Vulnerability can be defined as ‘the degree to which a system is susceptible to and unable to cope with, adverse effects of climate change, including climate variability and extremes’ (IPCC 2007). For example, a climate change resistant stance will promote the development of climate-independent sources of supply, an increase in the ‘buffer’ capacity between supply estimates and demand forecasts, or both. It may also look at demand-side measures that could reduce the supply volume required in an extreme drought. A climate change resistant stance might also risk-weight options in order to develop a portfolio that is less vulnerable to any changes in climate.
- A *climate change resilient stance* will try to reduce the vulnerabilities of urban water systems but also focus on increasing their adaptive capacity. Resilience can be defined as ‘the capacity of a system to absorb disturbance and reorganize while undergoing change so as to still retain essentially the same function, structure, identity, and feedbacks’ (Walker et al. 2004). A climate change resilient stance will promote the development of a diversity of supply sources as well as the range of available demand-side measures. It will also increase the adaptive capacity of the urban water system through means such as developing readiness options and drought contingency measures. These are measures that can be initiated at a predetermined point in a continuing drought. Both diversity and adaptive measures increase the flexibility of urban water systems faced with climate uncertainty.

These two perspectives should not be considered in ‘either/or’ terms, as both provide insights. They exist on a continuum, and the appropriateness of a particular stance will depend on the circumstances in the region.

4.3.2 Towards more adaptive planning

Even in regions where water planning is conducted with a strong climate change resistant stance, the uncertainties associated with climate change mean that planning is likely to become more adaptive.

Moves towards a more adaptive planning approach include considering:

- adaptive management
- developing adaptive measures
- more monitoring and evaluation
- reconsidering planning periods
- better integration of short-term (drought) and long-term planning
- governance for adaptive planning.

Adaptive management

Uncertainty about future climate creates a push towards adaptive management, which describes approaches that are flexible in their response to a range of possible futures, and are responsive in that they enable new understandings about uncertain conditions to feed back and determine the appropriate response (Jiggins and Röling 2000).

Adaptive management is likely to be valuable in urban water planning for regions where both the potential for climate extremes as well as the expected averages for climatic and hydrological variables are in doubt. It allows for measures to be initiated in response to an emerging and uncertain future. In urban water, this may involve having planned adaptive measures ready for ongoing droughts or extreme events. It can also mean incrementally and routinely adjusting the portfolio of supply- and demand-side options as the future unfolds.

Adaptive management is facilitated by having options that can be implemented in increments and timing that can be varied. Demand-side options are incremental by their nature, as they are implemented house by house or business by business. On the supply side, this means modular treatment technology such as desalination or potable water recycling plants, which can be initiated with relatively short lead times in order to meet the demand for water when the need occurs. Through the use of incremental and modular options, adaptive management can avoid the financial and other risks that are associated with decisions to build large-scale infrastructure based on anticipated climate change scenarios or demand forecasts that might not eventuate.

Developing adaptive measures

The preplanning of measures that can be deployed as events unfold is necessary to allow for adaptive management. Adaptive measures in the form of water restrictions are commonly used in water supply management. Contingency measures for emergency drought situations are also adaptive measures. Such measures are discussed in Section 4.5.3 under 'Drought planning'. Taken a step further, readiness options are supply- and demand-side options that are preplanned and are triggered at particular storage levels (much like restrictions). Readiness options are also discussed in Section 4.5.3.

More monitoring and evaluation

An adaptive approach to planning will require increased monitoring and evaluation of a range of parameters. It will also require more regular reviews of supply–demand plans, leading to a reconsideration of planning periods. These issues are addressed in Section 4.6.

Reconsidering planning periods

There is a need to reconsider long-term planning periods in the light of climate uncertainty. While a traditional urban water planning paradigm aims to plan up front for many decades, uncertainties about future climate render that aim less appropriate. Analysts may continue to forecast out many decades, but uncertainties amplify in the later years. Supply–demand plans that allow for changes as the future unfolds, rather than looking to meet community needs projected 50 years forward, will therefore prove advantageous in the long run.

Better integration of short-term (drought) and long-term planning

There is the potential to make appropriate short-term decisions that also align with long-term supply–demand goals. This would mean more integration of drought or contingency planning and long-term supply–demand planning. For example, a readiness option developed as an adaptive measure for drought, once implemented, may become the new long-term supply for a given urban area. In some locations, increased climate variability and an adaptive approach to supply–demand planning may even shift the planning paradigm. Instead of traditional supply–demand planning aimed at balancing supply and demand for many decades, an adaptive paradigm with supply- and demand-side options triggered by a series of droughts may emerge as a way in which the supply–demand gap is filled over time.

Governance for adaptive planning

Decision makers and the public commonly perceive adaptive management and the use of adaptive responses, particularly readiness options, as risky strategies. This is despite the potential of an adaptive approach to avoid the financial and other risks that are associated with a decision to build large-scale supply infrastructure based on an expected climate change scenario that may not eventuate. For this reason, well-defined and well-communicated governance arrangements and public engagement in planning and ongoing management are keys for success.

The community needs to be engaged with the planning processes. At least, the public must be kept informed about the existence of planned adaptive measures, such as readiness options. It also needs to know what to expect in planning decisions in particular circumstances, and also what will be expected of community members as water consumers in terms of water restrictions under particular conditions. Ideally, this community engagement will go further, to include a level of participation in planning decisions that builds trust. Without an engaged public that has been part of and trusts the planning process, a climate change response based on adaptive management and readiness options is likely to fail in the face of calls for new large-scale supply to 'secure' water supplies. An engaged public that understands the issues and uncertainties associated with climate change could potentially tolerate more regular drought response measures, as it will more clearly identify with the need for the response and understand the effects of its actions. Some of the issues involved in public participation in IRP are covered in Fane et al. (2010, in this document).

In addition to the challenge of public engagement, other challenges in relation to governance of adaptive planning in urban water include:

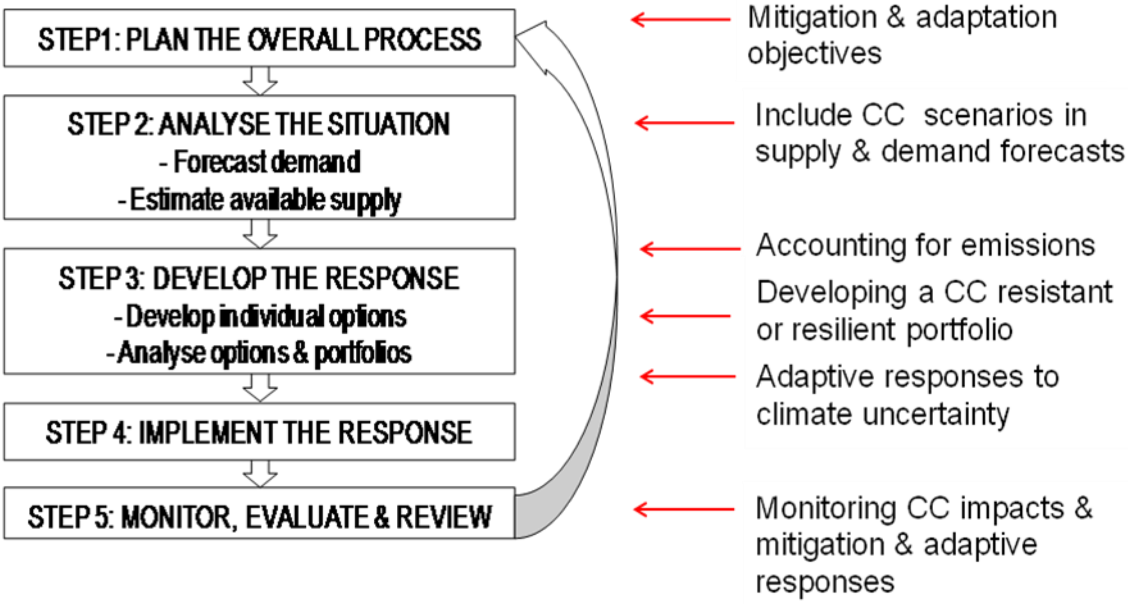
- decision makers' and some stakeholders' initial lack of understanding of adaptive planning approaches
- different jurisdictions' control over different aspects of the water cycle, making coordination difficult
- lengthy, complicated processes 'fleshing out' roles and responsibilities among involved jurisdictions and stakeholders
- the need to justify resourcing in terms of preparedness planning and the need for ongoing monitoring, rather than a capital works budget
- the availability of the required skills.

The potential for decision makers and stakeholders to change over time means that the communication of an adaptive approach to planning in a region is likely to be an ongoing process for the water planners involved.

4.3.3 Implications of climate change across the IRP process

As illustrated in Figure 4.2, climate change and the associated uncertainty about future climates have implications across the IRP framework. Those implications will need to be recognised in Step 1 ('Plan the overall process') in particular, so that stakeholders involved in the IRP process are aware of the full extent of the issues that climate change raises for supply–demand planning.

Figure 4.2 Implications of climate change across the IRP framework



In Step 1, climate change recasts the planning objectives in relation to urban water supply and demand. In many regions, water planning will be defined in terms of 'water security' in the face of climate change. However, supply–demand planners will need to consider both the mitigation and the adaptation aspects of climate change. They will also have to be cognisant of the various perspectives that they and other stakeholders bring to the process, as well as a potential need to be more adaptive in order to manage climate uncertainty.

In Step 2, climate change adaptation requires accounting for expected climate change impacts in projections of the long-term supply–demand balance. This involves incorporating the 'best estimate' climate change scenario into both the system yield and the demand forecast. Uncertainties about future climate can then be represented by high and low case climate change scenarios. These issues are addressed in Section 4.4.

A climate change resistant stance in Step 2 would be to take conservative baseline system yields and high demand, resulting in an increased buffer capacity. Naturally, this raises questions about the risk of overinvestment and system 'gold plating'. The selection of conservative baselines can have major implications for the level of financial investment and the timing of and need for supply augmentations. These implications should be made explicitly clear to stakeholders and decision makers.

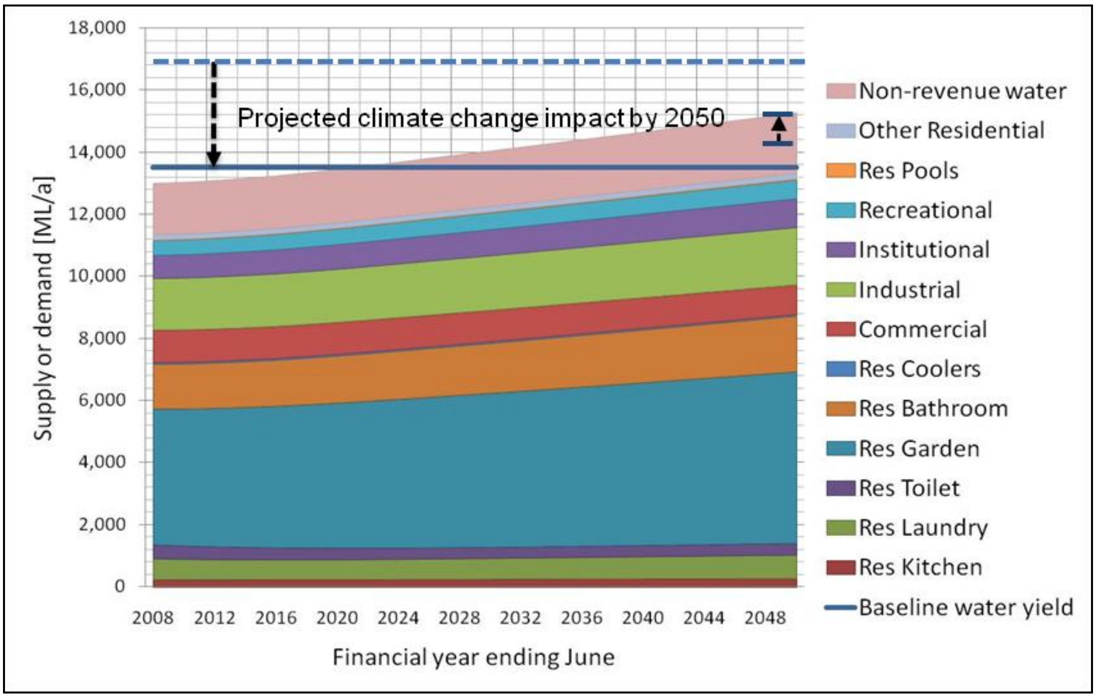
In Step 3, responding to climate change will mean developing a more climate change resistant or resilient portfolio of options. What this means in practice is likely to remain contentious for some time. For example, each of the four perspectives outlined in Figure 4.1 would lead to different conclusions about the most appropriate response. This paper outlines two elements that are relevant to various perspectives: increasing portfolio diversity and developing adaptive measures. However, it is evident that there is more work to be done on the question of determining the most appropriate response to climate change for a given region.

Step 4 of the IRP framework ('Implementing the response') is not specifically covered by this paper, but Step 5 ('Monitoring, evaluation and review') is discussed in Section 4.6. In general, in the face of climate change there will be an increasing role for monitoring and evaluation. This is a mechanism both for measuring the effectiveness of the implemented responses and for managing uncertainties associated with climate change.

4.4 Analyse the supply–demand situation

Step 2 in the IRP framework is 'Analyse the situation'. It involves making an assessment of the yield of the existing water supply and a forecast of future water demand, and is the crucial point in developing a picture of the long-term supply–demand balance for a region. Figure 4.3 presents a hypothetical regional supply–demand balance and the impacts of projected climate change. The indicated 20% decrease in available yield could be considered minor compared to the forecast decrease in some regions.

Figure 4.3 Illustration of a regional supply–demand balance



Generating climate change scenarios and incorporating them into forecasts of supply and demand are a key analytical means by which climate change can be incorporated in the IRP process. A range of methods exist for this. The available approaches and the questions raised by them are discussed below, along with the selection of scenarios and specific issues associated with demand forecasting.

4.4.1 Generating climate change scenarios

The three main bases that can be used for generating climate change scenarios for use in urban water planning are listed in Ashbolt and Maheepala (2008):

- scenarios based on GCM simulations and regional 'downscaling'
- hypothetical scenarios of postulated changes in specific climate variables or extensions of current climate trends
- analogue scenarios, which can be based on selected parts of the historical climate record or may utilise climate records from a different location.

The most rigorous and widely accepted approach is to base climate change scenarios on GCM simulations and to downscale the global climate projections to the regional level by various means. Where downscaled data is unavailable or does not appear to represent local conditions very well, an approach based on a hypothetical or analogue scenario may need to be considered.

Scenarios based on GCM downscaling techniques

GCMs generate a set of global climate data based on an understanding of physical atmospheric–oceanic processes. The models represent various Earth systems, including the atmosphere, oceans, land surface and sea-ice. From 1880 to 2000, the models simulate the climate, including forcing from observed atmospheric levels of GHGs and aerosols. After 2001 and up to 2100, simulations are based on the range of future GHG and aerosol emissions scenarios described in IPCC (2000).

The grid size of a GCM is coarse (~100 to ~400 kilometres) compared to the regional and local catchment scales at which urban water planning is carried out. Therefore, various extensions of GCM techniques (downscaling) have been developed to improve the resolution of the climate data generated, usually down to 10–20 kilometres. Major downscaling methods include:

- *statistical downscaling*, the simplest method of which is to perturb historical climate data series by change factors obtained from a GCM; other methods are to apply relationships between the large-scale atmospheric variables (predictors) obtained from GCM and the local or regional climate variables (predictands)
- *dynamical downscaling*, which refers to the use of regional climate models that are run with large-scale and lateral boundary conditions from GCMs to produce higher resolution outputs.

See Fowler et al. (2007) for a review of downscaling methods and Box 4.3 for details of simplified downscaling approaches that can be applied only to rainfall and runoff data**.**

The advantages of statistical downscaling are that it is computationally efficient and therefore relatively cheap compared to other downscaling techniques, and that it can provide point-scale climate variables from GCM outputs and directly incorporate observations (historical climate data) into the method (Ashbolt and Maheepala 2008). Its disadvantages include its requirement for a long and reliable observed historical data series for calibration, its dependence on the choice of predictors; and the potential non-stationary nature of the relationship between predictors and predictands. The performance of statistical downscaling will vary with grid size, climatic region and season.

The advantages of dynamical downscaling include its ability to produce an output based on physically consistent processes. Its disadvantages include its computational intensity, the limited number of scenario ensembles that are available, and its strong dependence on GCM boundary forcing.

Box 4.3: Simplified downscaling approaches for rainfall and runoff

Hydrological models used to estimate climate change impacts on runoff commonly require a daily rainfall series. Future rainfall series, informed by GCMs, can be generated in a number of ways, including statistical and dynamical downscalling. However, the application and calibration of statistical downscaling methods can be fairly laborious, and dynamic downscaling can be very computationally expensive. Another method, which is simpler and cheaper to run, is the empirical scaling method. This has been widely used in studies on the effect of climate change on runoff (Fowler et al. 2007), including the latest CSIRO Murray–Darling Basin Sustainable Yields Project (Chiew et al. 2008) and the Northern Australia Sustainable Yields Project (CSIRO 2009). There are three simple empirical scaling methods:

- *Constant scaling*. The historical daily rainfall series is scaled by the relative difference between the GCM simulations of future climate and the historical climate. All the daily rainfall in a given season is scaled by the same factor for that season. Thus, constant scaling assumes that there is no change in the future daily rainfall distribution.
- *Daily scaling*. As in constant scaling, the historical daily rainfall series is scaled by the relative difference between GCM simulations for the future and historical climates. However, daily scaling takes into account changes in daily rainfall amounts differently. First, for each season the daily scaling factors are applied to scale the different daily rainfall amounts for a future climate relative to a present climate. The entire series is then scaled, using a different constants factor for each of the four seasons, to ensure that the mean rainfalls in the four seasons are the same as those in constant scaling (see Chiew et al. 2008 for details).
- *Daily translation*. The GCM future daily rainfall series is translated to the observed fine-resolution grid rainfall series using the relationship established between the historical-scale rainfall and the observed fine-resolution grid rainfall (Mpelasoka and Chiew 2009).

Because these methods are simple to use, they can be easily applied across large regions, for different GCMs, and for various GHG emissions scenarios. They can therefore take into account the large uncertainties associated with global warming and local climate projections (see Section 4.4.2 for details about how to represent the uncertainties). Mpelasoka and Chiew (2009) have found that the difference between mean annual runoff simulated with future daily rainfall series obtained using the constant versus daily scaling methods is generally less than 5%. This is relatively small compared to the range of runoff results from the different GCMs (30%–40%).

Hypothetical and analogue climate change scenarios

Downscaling of GCMs provides the most comprehensive and physically based approach to understanding the impacts of climate change on water supply and water demand. However, there are no comprehensive GCM studies across all parts of Australia, and the approach requires a relatively data- and time-intensive exercise for smaller water utilities.

In the absence of GCM-generated climate data, hypothetical and analogue climate change scenarios may be used to examine the sensitivity and relative hydrological impact of changes in climate (Ashbolt and Maheepala 2008). Hypothetical scenarios may take the form of extrapolations of historical trends, simplified proportional changes in local climate variables (for example, plus or minus 10%) based on global climate change forecasts, data sourced from various climate models, or other expert judgment. Analogue scenarios use data from a part of the historical climate record, from other locations or from the deep past (such as paleoclimate analogues) as proxies for future climate change. Critically, either hypothetical or analogue climate change scenarios need to represent a plausible trajectory for future climate and hydrological variables.

Lacking comprehensive GCM studies across Australia, in recent years some utilities have incorporated climate change impacts directly as hypothetical scenarios at the yield forecasting stage. In these cases, supply system yields have been reduced and supply systems de-rated from levels indicated by the historical record. Adjustments have been stepwise or linear adjustments to the baseline yield forecast (that is, a percentage decrease or a yearly percentage reduction in the forecast yield, relative to the historical record). The bases for these hypothetical scenarios are expert judgment that recent observed streamflows represent step changes in runoff or that current trends represent the trajectory for future system yield in the region.

Notwithstanding these examples, hypothetical and analogue climate change scenarios are probably best made at the level of the climate data because climate change will affect climatic variables, and therefore the plausibility of climate scenarios will be more easily assessed at this point. The affect of the hypothetical or analogue climate data can then be modelled in terms of effect on runoff and streamflow into water storages or replenishment of groundwaters. On that basis, the impact on system yields can then be analysed.

A risk with hypothetical and analogue scenarios is that, without a basis in physical atmospheric processes, they can be unrealistic and not represent a reasonable trajectory for future climate. Planning to meet an apparent supply–demand gap based on incorporating a hypothetical climate change scenario into the supply and demand forecast therefore creates a significant risk of overinvestment. As more GCM studies are conducted across Australia, it is expected that hypothetical climate change scenarios will not be incorporated into the base-case forecasts of the supply–demand balance. However, they are likely to continue to have a role in exploring the sensitivity of urban water systems to climate change and in scoping the impact of possible changes in climate.

4.4.2 Selecting climate change scenarios

Climate change is expected to affect both sides of the supply–demand balance, although the impacts on demand are likely to be less than the impact on supply in most regions. For example, the climate change impact study carried out in Melbourne (Howe et al. 2005) showed that, for a medium emissions scenario, the expected increase in urban demand in the Melbourne region was about 3% compared to the expected reduction in system inflow of about 20%. To estimate the impact of climate change on supply and demand, most studies use a predictive approach. This means taking a climate change scenario in which climate variables have been generated and feeding the synthesised climate or hydrological data into water system models. Depending on the water planning context, this may be a single-component model or a model using a series of components (Ashbolt and Maheepala 2008). A single-component model will use the data from a climate change scenario in order to quantify a particular impact; for example, a rainfall–runoff model is used to quantify the potential impact of climate change on streamflow. In another context, the scenario data will be used to quantify a series of impacts, such as impacts on rainfall–runoff, future demand and system yield in different models (Maheepala and Perera 2003, Maheepala et al. 2003).

In either case, the uncertainty about future climate as a result of climate change will need to be represented through the selection of a set of climate change scenarios. This can be done via the selection of high and low case climate change scenarios, as well as a medium case scenario (Howe et al. 2005). The medium case scenario should represent the best estimate of climate change for the region in question and be included in the base-case forecasts of supply and demand. The high and low cases should represent wet and dry extremes for future climate. These cases can be used for testing longer term water planning.

As well as the impacts of climate change on the longer term supply–demand balance, water planners should also consider how climate change may affect planning for adaptive measures, whether those measures are readiness options or drought contingency measures. In some studies, a distinct worst case scenario may therefore be considered alongside the other climate change scenarios to test adaptive planning. In other instances, the worst case scenario will be the low case (dry extreme) climate change scenario.

Table 4.2 summarises the different types of climate change scenarios and indicates their recommended use in supply–demand planning.

Table 4.2: Climate and climate change scenarios

Type of climate change scenario	*Recommended use in supply–demand planning*[a]
Medium or 'best estimate' climate change scenario	To represent the most likely climate change scenario for the supply–demand balance
Extreme wet and dry future climate change scenarios	To test high and low cases in the supply–demand balance to account for uncertainty in climate change projections
Worst case climate change scenario	To test adaptive planning, including readiness strategies and drought contingency plans

a These recommendations were one outcome from a workshop held in November 2008 with leading water industry supply–demand planning practitioners.

In some regions, natural climate variability is also a major factor. The potential for shifts in climatic mode can be analysed by selecting different climate baselines to represent alternative climate modes. Climate change scenarios are then overlaid on top of the different baselines.

Representing the uncertainty in climate change projections

As discussed in Section 4.2.1, there are three main sources of uncertainty in projections of climate change: future GHG emissions, the sensitivity of the global climate to GHG concentrations, and how changes at a global level will translate to changes at the regional level.

The first uncertainty can be addressed by considering possible future emissions trajectories and the resulting GHG concentrations, as presented in the IPCC's special report on emissions scenarios (IPCC 2000). The second can be addressed by considering the rate of warming in different climate models. The third can be addressed, at least in part, by considering the differing spatial patterns of climate change in multiple climate models.

As an illustration, CSIRO Murray–Darling Basin (MDB) Sustainable Yields Project (Chiew et al. 2008) used three GHG emissions scenarios for ~2030 relative to ~1990: high emissions, medium emissions and low emissions. The three trajectories were inferred from the IPCC's fourth assessment report (IPCC 2007) and the latest climate change projections for Australia (CSIRO and BoM 2007a). Archived monthly simulations from 15 IPCC GCMs were then analysed to estimate change in rainfall and other climate variables per degree of global warming. Daily rainfall simulations from the 15 GCMs were also applied. The result was 45 plausible climate change scenarios.

From the 45 climate change scenarios, uncertainty about future climate was then represented by selecting three scenarios. These were the best estimate, an extreme dry case and an extreme wet case. The best estimate was the median result across the region from the 15 GCM results for the medium GHG emissions scenario. The extreme dry case was taken to be the second driest result from the high GHG emissions scenario, and the extreme wet case was taken as the second wettest result from the high GHG emissions scenario. Box 4.4 provides further details on scenario development in the MDB Sustainable Yields Project.

A similar approach was used in the climate change impact study carried out by the CSIRO for the Melbourne region (Howe et al. 2005), which used 11 GCMs and three GHG emissions scenarios (that is, 33 plausible climate change scenarios). Maheepala and Perera (2003) also used a similar approach to quantify the potential climate change impacts on the Benalla water supply system in north-east Victoria. They used eight GCMs and four GHG emissions scenarios (that is, 32 plausible climate change scenarios).

This approach aligns to common practice to date, which has been to define the best estimate as the median results from a range of GCMs based on the medium GHG emissions scenario and the extreme dry and wet estimates as the second driest and second wettest results from the range of GCMs for the high GHG emissions scenario (for example, Chiew et al. 2008). However, since we are tracking on or above the IPCC's high GHG emissions scenario, it may be more reasonable, as Moran (2008) suggests, to take medium results from the high GHG emissions scenario as the best estimate in water planning.

It is worth noting that for the next 20 years or so the uncertainties in projected regional climate change will be dominated by the differences between the results from the various climate models, rather than differences between emissions trajectories, whereas beyond 2030 there is greater uncertainty about the emissions trajectory.

Worst case scenarios

A worst case scenario is by definition a low probability event. Traditionally, a worst case climate scenario would be defined by an annual exceedance probability and calculated using a stochastic approach based on historical hydrological data. Under climate change the nature of extreme events is likely to alter, and historical climate data can no longer provide a direct indication of the extreme events that may occur in the future.

Choosing a worst case scenario under the uncertainty associated with climate change is therefore more difficult, and there is no clear consensus within the water industry on what represents a reasonable worst case. There is also disagreement about the role of worst case scenarios in supply–demand planning. The question remains a significant issue, as the results of worst case scenario modelling have the potential to play a major role in driving responses to climate change in the water industry.

This paper strongly recommends against the use of worst case climate change scenarios in establishing a supply–demand balance. What it recommends is to use worst case scenarios in testing adaptive planning, including readiness strategies and drought contingency plans.

Some of the approaches used by Australian water utilities to develop worst case climate change scenarios have included using:

- a repeat of the climate sequence of the worst drought on record for the region
- a repeat sequence of the worst year on record
- the climate sequence of the worst drought on record, with a medium or extreme dry climate change prediction overlaid.

Another method that has been used for defining worst (and best) case scenarios is a probabilistic risk analysis of changes to a variable of interest (such as runoff) using a range of climate scenarios applied to a range of baselines. As an example, Jones and Page (2001) considered the long term (1890–1996), a drought-dominated period (1890–1947) and a flood-dominated period (1948–1996) to assess the risk of climate change for the water resources of the Macquarie River catchment in New South Wales. Their results showed that a combination of drought-dominated conditions and climate change produced worst-case outcomes for streamflow in the Macquarie Basin.

When establishing a worst case climate change scenario, necessary considerations include the following:

- *The worst case will vary across regions*. This requires an acknowledgment that the historical climate record and experience in the location still have much to tell us. They need to be considered together with the climate change projections.
- *Care must be exercised to preserve the internal consistency of scenarios within climate model projections*. Because climate variables such as temperature, rainfall, evaporation and humidity are highly interactive, one cannot use the most pessimistic rainfall projection from one climate model and pair it with the most pessimistic temperature projection from another to identify the worst possible outcome from a hydrological impact model. Instead, estimates of impacts should first be calculated independently for each climate model under consideration. The results can then be used to identify the worst or best outcome.

- *There are likely to be 'critical thresholds' for the system in question*. A critical point is that point at which an activity or system faces an unacceptable level of harm (Jones and Page 2001). By delineating the coping range of climates (that is, the range of climate variability that is considered manageable, given the current system and current adaptive planning) from that part of the range in which the system is vulnerable. The question can then be asked, 'Do climate scenarios within the vulnerable range represent reasonable worst case scenarios for climate change?'

Representing uncertainty due to climate variability

In some regions of Australia, the continuing pattern of lower than average rainfall and inflows to storages has led to supply systems being de-rated based on the extrapolation of current trends. However, it remains unclear whether the observed drying trend over the past decade in particular regions is part of natural climate variability, the result of human-induced climate change, or a combination of the two.

As discussed in Section 4.2.1, the Australian climate naturally shows modes of decadal and multidecadal variability, and that variability results in a level of uncertainty about recent observed climate trends. Significantly, the different modes within this variability can have a large influence on the water supply systems (Vives and Jones 2005). The choice of the climate or hydrological baselines used in constructing the supply–demand balance is then critical.

The selection of a conservative baseline which assumes that the observed drying trend will continue will have major implications for the need for supply augmentations and the timing of any augmentation, and therefore the level of financial investment required. Where a conservative baseline is selected, the potential financial and community perception risks of that choice should be made explicit to stakeholders and decision makers, together with the potential direct supply system risks. For example, selecting a 10-year period of lower than average rainfall or inflow data as a baseline carries a risk of overinvestment if rainfall were to increase again in coming decades. Some experts consider that 30 years should be the minimum length for a historical baseline climate or hydrological scenario (see also Hulme et al. 2009 for a review of statistical and social constructions of 'normal' climate).

In situations of potential modal shift, it will be prudent to consider a range of baseline periods in the analysis of the supply–demand balance. Each baseline should be based on a period of historical data. Climate change scenarios (medium, extreme and potential worst case) can then be overlaid. Such an approach accounts both for uncertainty linked to natural climate variability and for uncertainty linked to climate change.

Box 4.4: Estimating the impact of climate change on water availability—an example from the Murray–Darling Basin Sustainable Yields Project

The MDB Sustainable Yields Project included the most comprehensive hydrologic modelling undertaken for the entire MDB to date. The project included modelling of rainfall–runoff and groundwater recharge across the MDB and fully linked modelling of all major MDB river systems and their connections to groundwater systems. The aim of the project is to estimate current and likely future (~2030) water availability in comparison to that required to meet the current levels of extractive use.

The resource development and climate change scenarios considered were as follows:

1. *A baseline scenario* (for comparison with other scenarios). This was the historical climate from mid-1895 to mid-2006, and the current level of water resource development.
2. *A scenario based on the climate of 1997 to 2006 and current resource development*. This scenario was used to evaluate the consequences of a long-term continuation of the recent severe drought in south-eastern Australia and to provide a reference point for the climate change scenarios.
3. *A scenario based on future climate (~2030) and current resource development*. This encompassed the range of possible future climates based on three global warming scenarios or emissions trajectories (low, medium, and high) and 15 of the GCMs included in the IPCC's fourth assessment report. Forty-five future climate change scenarios, each with 112 years of daily climate sequence, were then used for the rainfall–runoff modelling. The climate change scenarios came from scaling the 1895 to 2006 climate data to represent the climate around 2030 relative to ~1990. The approach adopted was to use both seasonal and daily factors to scale historical daily data, in order to account for changes in the future mean and changes in future daily rainfall distribution.
4. *A scenario based on future climate (~2030) and future resource development*. Development includes growth in farm dam capacity, expansion of commercial forestry plantations and increases in groundwater extraction.

All four scenarios assumed the continuation of the existing surface and groundwater sharing plans implemented by states.

The reporting focused on:

- the median of the range, which is median results from the 15 GCMs for the medium global warming scenario
- the uncertainty, which is reported as a 'wet extreme' and a 'dry extreme' in the range (the wet and dry extreme estimates are the second wettest and driest results from the high global warming scenario).

Key results included the following:

- The south of the MDB was in severe drought from 1997 to 2006, and the catchment runoff in the southernmost parts of the MDB was the lowest on record. This event would occur only once in more than 300 years without climate change. Such conditions will become increasingly common.
- The impacts of climate change by 2030 are uncertain, but surface water availability across the entire MDB is more likely to decline than to increase. A decline in the south of the MDB is more likely than in the north. In the south, a very substantial decline is possible; in the north, significant increases are possible.

Source: Chiew et al. (2008).

4.4.3 Specific issues for demand forecasting

Climate change will be likely to affect demand, although the magnitude of any change in demand will depend on a number of interconnected factors. Impacts on demand will depend on a combination of climatic variables, including temperature, rainfall, humidity and evaporation, as well as current patterns of water use.

The sensitivity of future demand to climate change can be gauged from the current seasonality of demand. End-use based analysis is one approach for understanding the effects that climate change may have on water demand because certain end-uses will be particularly affected. Such an approach would involve considering how climate change will affect particular water-use components and the impact that would have on the overall urban water demand picture. For example, in the residential sector the two key areas will be seasonal demand for outdoor water use and evaporative air conditioner use. Similarly, in the non-residential sector, outdoor water use and water use in cooling towers and evaporative coolers could be expected to increase under climate change in regions where current summer demand is high. Table 4.3 summarises the end-use components of residential and non-residential demand that could be affected by climate change.

Table 4.3: Residential and non-residential water demand affected by climate change

Sector and end-use component	*Potential reasons for change*
Residential sector	
Outdoor demand	Outdoor water demand could increase in the absence of temporary or permanent water restrictions due to increased irrigation resulting from increased evapotranspiration and reduced soil moisture in drier climates. Outdoor water demand could also increase because of an increasing number of pools and increased evaporation losses. Outdoor demand could potentially decrease in regions that become wetter or have high levels of humidity due to climate change, particularly if increased rain and humidity correspond to current periods of high use.
Evaporative air conditioners	Increased average daily temperature in summer and/or increased number of days above 30°C will lead to increased evaporative air conditioner use in the regions where they are prevalent.
Non-residential sector	
Outdoor water use	As for residential outdoor demand, non-residential outdoor demand could increase or decrease.
Cooling towers	Increased average daily temperature in summer could lead to increased use of cooling towers in non-residential properties.
Evaporative air conditioners	In smaller non-residential properties, increased average daily temperature and/or increased number of days above 30°C will lead to increased evaporative air conditioner use in the regions where they are prevalent.

The effect of climate change on water demand will vary between locations (for example, impacts in inland regions can be expected to be higher than in coastal regions). Some utilities have investigated the changes in the demand profile that might be expected from climate change in their jurisdictions. For example, the Victorian Department of Sustainability and the Environment expects demand increases across Victoria of 1%–6% due to climate change. Sydney Water has estimated demand increases of approximately 1% relative to current consumption, although there can be differences between coastal and inland suburbs in a region as large as Sydney. Significantly, the influence of climate variables other than rainfall and temperature can be important. In some regions, humidity will offset some demand caused by increased temperature.

Total water demand is influenced by a range of other factors, including demand-management programs, urban consolidation and land-use changes. Therefore, in any particular jurisdiction, demand impact assessment needs to be based on a local end-use profile and expected region-specific climatic changes. Even though the percentage changes may be relatively small, it will be prudent in most locations to consider the impacts of climate change on demand because the volumes could be significant, especially during drought periods. End-use analysis can provide a basis for such investigations.

In inland regions, the impacts of climate change on agricultural water demand might also become a factor for urban water planners. While agricultural allocations are set by a government department separately from urban water planning, changes to agricultural allocations in response to changing watering requirements could affect the supply available for urban water needs.

4.5 Developing the response

'Develop the response' is Step 3 in the IRP framework. It involves not only the design of individual supply-side and demand-side options and their assessment, but also the development of a suite or portfolio of options that can ensure that the community has a safe, reliable, sustainable and cost-effective supply.

Climate change and uncertainty about future climate have significant implications both for the options that should be considered and for how options and portfolios are assessed. First, the mitigation imperative means that the response developed must take into account the GHG emissions that could be expected to result from implementation. Second, the objective of climate change adaptation requires the development of more resistant or resilient portfolios. Two aspects of this goal are discussed below: increasing portfolio diversity and developing adaptive measures.

Although not discussed in this paper, in the same way that best estimate climate change scenarios are included in the supply–demand balance, expected changes to climatic and hydrological variables should be factored into the yield estimates for options such as new storages, rainwater tanks and groundwater. In many areas, the climate change scenarios developed for establishing the supply–demand balance (discussed in Section 4.4) may be appropriate for that task. In others, regional differences, particularly between coastal areas and inland catchments, will need to be accounted for.

4.5.1 Accounting for greenhouse gas emissions

To meet an objective of mitigating the GHG impacts of urban water services requires an understanding of the energy use in current service provision and the likely emissions that would result from potential demand- and supply-side options. It also includes considerations in relation to Green power as a means of avoiding energy-related emissions.

Energy used in existing urban water supply

Urban water service provision requires energy for water supply (treatment and distribution), and wastewater disposal (sewage collection, pumping and treatment). The energy intensity of water services in a selection of major Australian cities is given in Table 4.4. The energy intensities will increase in the future as new energy-intensive supplies are brought online.

Table 4.4: Summary of the energy intensity of water supply and wastewater disposal in Australia cities in 2006–07 (MWh/ML)

	Sydney	*Melbourne*	*Brisbane*	*Gold Coast*	*Perth*	*Adelaide*
Water supply	1.03	0.09	0.68	0.21	0.98	1.84
Wastewater disposal	0.47	1.13	0.57	1.00	0.71	0.69
Total for water service provision	1.49	1.22	1.25	1.21	1.70	2.52

Source: adapted from Kenway et al. (2008).

Even before the latest supply augmentations, a rising trend in the energy intensity of water supply was evident in Australia. Table 4.5 shows the increase in energy intensity of water supplies in Sydney, Perth and Adelaide in recent times.

The increasing energy intensity of water supplies highlights the need to account for energy use and subsequent GHG emissions when developing a portfolio of supply- and demand-side options. It also points to the need for new water infrastructure to be designed with energy efficiency in mind.

Table 4.5: Change in the energy intensity of water supply in Sydney, Perth and Adelaide

City	*Year*	*Energy intensity (kWh/kL)*	*Comments*
Sydney	2000–01	0.25	
	2006–07	1.03	Interbasin transfer (Shoalhaven River)
Perth	2001–02	0.56	
	2006–07	0.98	First desalination plant
Adelaide	2005–06	0.85	
	2006–07	1.84	Interbasin transfer (Murray River)

Source: Retamal et al. (2009), adapted from Kenway et al. (2008).

Alongside the energy used by water utilities in providing water services, substantial energy is used in water heating. Recently published work by Kenway et al. (2008) found that residential water heating used on average 6.5 times the energy used to deliver urban water services. This ratio varied between cities, from 4.7 in Adelaide to 11.2 in Melbourne. As a result, measures reducing demand for hot water (for example, targeting showers or clothes washers) will have large energy-saving benefits relative to the energy used by utilities. Helping customers reduce energy use through demand-management programs aimed at hot water usage is an excellent opportunity for water utilities to contribute to GHG mitigation. However, it should not be viewed as an alternative to addressing the rising amounts of energy used in the provision of water services.

Energy use and GHG emissions for different options

Different types of supply-side and demand-side options will have different ramifications for energy consumption and GHG emissions. In general, supply-side options will increase energy demand and GHG emissions. Some source-substitution options that are usually considered as demand-side, such as rainwater tanks and non-potable effluent reuse, will also have an energy demand and associated GHG emissions. Demand-management measures that reduce the amount of water consumed (that is, water efficiency options) will save energy and reduce greenhouse gas emissions. Measures that reduce hot water consumed will have the most substantial energy and GHG savings, as outlined in the previous section. Table 4.6 gives indicative energy consumption figures for various types of supply- and demand-side options.

Table 4.6: Indicative energy consumption/savings from different options

Type of option	*Energy use*	*Indicative energy intensity*[a]	*Data source*	*Comments*
Supply-side				
Desalination	Increase	3.5–4.0 MWh/ML	Kenway et al. (2008)	This figure was given in the source document in GJ/ML.
Intercatchment transfer pipeline	Increase	0.07–1.75 MWh/ML	Kenway et al. (2008)	Energy demand due to pumping.[b] Need to assess unit energy demand in each specific context, as this figure will vary depending on factors such as topography and length of pipeline.
New dam	Increase	Varying	–	Potential energy demand due to pumping. Need to assess in each specific context. Direct reservoir surface emissions are likely to be more much significant than increased energy use.
Demand-side				
Demand management	Saving	Approx. 1.21–2.52 MWh/ML (not including water heating)	Kenway et al. (2008)	Energy saving from energy used by the water utility
Rainwater tanks	Increase	0.9–4.9 MWh/ML	Retamal et al. (2009)	Energy for pumping water from tank to household.
Non-potable water reuse	Increase	1.6–2.9 MWh/ML[c]	Kenway et al. (2008)	This figure was given in the source document in GJ/ML.

a The figures provided here are indicative only; practitioners should familiarise themselves with the assumptions and limitations described by the original authors.
b Estimated, based on energy intensity range for conventional water pumping given in source document.
c Including both tertiary treatment and reverse osmosis processes.

The GHG emissions (or avoided emissions) of potential options can be calculated from the expected energy consumption or saving. Electricity supplies vary in greenhouse gas intensity ($kgCO_2$-e/kWh) across the country. Greenhouse gas intensities are published by the Australian Department of Climate Change in *National Greenhouse Accounts (NGA) factors* (DCC 2008) and are given in Table 4.7.

The significant GHG savings that result from avoided customer water heating can be quantified by calculating the energy required to heat water from an average supply temperature to an average hot water temperature used by customers.[1]

[1] From first principles, the energy to heat water from 20°C to an average usage temperature of 42°C is approximately 25.9 kWh/kL for electric water heating and 93.1 MJ/kL for gas water heating. Note that this does not account for water heating inefficiencies and energy losses. The different mixes of water heating systems (electricity, gas, solar) across different states and territories need to be accounted for. The average GHG intensity for electric water heating is the same as given in Table 4.5; for gas water heating, an average Australia-wide figure of 64.5 $kgCO_2$-eq /GJ can be used.

Table 4.7: GHG intensities of electricity production across Australia

State/territory	*Average greenhouse gas intensity of electricity (kgCO_2-e/kWh)*
New South Wales	1.06
Victoria	1.30
Queensland	1.04
South Australia	0.98
Western Australia	0.97
Australian Capital Territory	1.06
Northern Territory	0.91

Source: DCC (2008).

Surface GHG emissions from water reservoirs are an issue for water supply planning that is becoming more widely acknowledged (St Louis et al. 2000, IPCC 2006ab). These emissions have been largely neglected in the past, although new research is indicating that the level of GHG emissions could be significant in some cases. As Hall et al. (2009) state in their study of energy and GHG emissions for the South East Queensland Water Strategy:

> Diffuse greenhouse gas emissions are potentially much greater than emissions from energy use for the [urban water] sector—although the data currently has a very high level of uncertainty. The main sources of diffuse emissions include reservoirs as well as wastewater treatment and handling.

The extent of methane and carbon dioxide surface emissions from water storage reservoirs in Australia is currently unknown. Worldwide, however, reservoir surface emissions are considered a significant source, contributing approximately 7% of human-induced GHG emissions (St Louis et al. 2000).

Methane and carbon dioxide emissions result from the decomposition of vegetation and soil carbon in the area inundated by the reservoir. More organic material can also be washed into the reservoir over time and this then also decomposes. A combination of carbon dioxide and methane is released from the surface of the water storage. Methane surface emissions are of particular concern because methane has a global warming potential 72 times that of carbon dioxide over a 20-year timeframe, and 25 times that of carbon dioxide over a 100-year timeframe (IPCC 2007). The IPCC provides a methodology for estimating reservoir methane and carbon dioxide surface emissions (IPCC 2006b).

Only limited Australia-specific data exists on reservoir emissions, and the available data indicates a high level of uncertainty. For example, estimates for the reservoirs serving south-east Queensland by Hall et al (2009) ranged from over 1 800 000 tonnes of carbon dioxide equivalent (t CO_2-e) per year to approximately 100 000 t CO_2-e per year. It is known that reservoir surface emissions will initially be higher from a new storage and then decrease with the age of the reservoir. Despite the uncertainty, reservoir surface emissions (particularly methane) are potentially a very significant source of GHG emissions for urban water. It is critical that the potential is assessed when new water supply dams are proposed in Australia.

Using renewable energy or Green power

Many water utilities that have recently proposed energy-intensive desalination plants have stated that they will purchase Green power or build renewable energy capacity to avoid the GHG emissions that would otherwise be generated. Green power involves paying a premium for electricity that is accredited as renewable. The additional cost will need to be paid over the operational life of the infrastructure. The additional cost of Green power reflects the value of the renewable energy certificates (RECs) that are generated when an accredited renewable energy scheme generates electricity. The RECs are surrendered when the Green power product is sold to a customer. Critically, a water utility that decides to build its own renewable energy scheme cannot sell the RECs generated and still claim the electricity generated as renewable. This would be a ‘double counting’ of the renewable energy.

For example, this problem has arisen in Perth with the renewable energy developed to power the Kwinana desalination plant. It was widely advertised that the desalination plant would be powered via the Emu Downs wind farm (Macgill et al. 2007). However, the RECs generated by the wind farm were on-sold to an electricity supplier. The energy generated by the wind farm could not then be counted as new renewable power by the desalination plant, because if the electricity supplier had not bought RECs from the water utility it would have needed to generate other renewable energy to meet its statutory requirement under the Mandatory Renewable Energy Target. The RECs from the desalination plant wind farm have simply displaced other renewable energy that would have to have been built (Macgill et al. 2007).

Organisations wishing to offset their electricity-related GHG emissions through the purchase of renewable electricity should do so in accordance with the National Carbon Offset Standard. The standard was released on 24 November 2009 and came into operation on 1 July 2010. Green power and other renewable energy purchases can be treated as zero-emissions sources of electricity under the standard.

Aside from double counting, a major problem with using renewable electricity is that it can be used as justification for building infrastructure that is operationally energy intensive and will leave a legacy of high energy requirements. The implications for a water utility's future operational costs in a future in which rising energy costs are highly likely cannot be ignored. Even if Green power is not sourced from new supplies, under the Australian Government's proposed Carbon Pollution Reduction Scheme, or any similar scheme, GHG emissions incur a cost, which will be passed on from energy generators to energy consumers through increased energy tariffs (see Box 4.5).

Where there is an intention to power new supply infrastructure with renewable energy, that decision effectively places a dollar value on GHG emissions and GHG abatement. In order to maintain an equivalent analysis of all options, that value should be translated through the options assessment. In other words, the value of GHG abatement that is included as a cost for the supply-side options should be carried through as a benefit for demand-side options. For example, a decision to power a desalination plant with renewable energy will increase the operating costs of that option. In contrast, demand-management measures such as household retrofits will reduce energy consumption and GHG emissions through avoided water and wastewater and avoided customer water heating. An options comparison including desalination and retrofits should give an equivalent value to the energy demand and GHG emissions avoided by one and abated by the other.

Box 4.5: The Carbon Pollution Reduction Scheme

Under the Australian Government's Carbon Pollution Reduction Scheme (CPRS), as orginally proposed, GHG emissions from energy generation will incur additional costs. Carbon costs will be imposed on all generators fuelled by fossil fuels. Those costs will be passed on to consumers, including water utilities, through higher electricity and other energy prices. For example, the government estimates that household electricity prices will increase by around 19% over the first two years of the CPRS (to 2012–13), with further small increases over subsequent years.

Some water utilities pay lower than average rates for their electricity use. Under the CPRS, the cost of emissions is likely to be added to the price of electricity in a manner that is proportional to energy use. Therefore, the price increase that water utilities face for electricity under the CPRS might be expected to be marginally higher than those faced by the average customer.

A CPRS would also change the prices of other goods and services, including construction materials and petrol. Carbon cost will be embedded in the prices paid for those goods. Goods that are emissions intensive to produce will generally become more expensive. It remains uncertain when, or whether, the CPRS as orginally proposed will be introduced; however, some form of Commonwealth scheme placing a cost on carbon pollution is likely.

The Water Services Association of Australia (WSAA 2009) summarised the main impacts of the CPRS and related policies, such as the National Energy Greenhouse Reporting Scheme, on the water industry as:

- higher energy prices
- the need to purchase permits for fugitive GHG emissions from facilities emitting over 25 000 tonnes of CO_2-e per year (such as sewage transport systems and treatment plants) and treated-effluent disposal to receiving waters
- uncertainty about carbon offsets, renewable energy and Green power, and what can be claimed about them.

4.5.2 Developing a diverse portfolio

Climate change and climate uncertainty bring to the fore questions of portfolio diversity. A diverse portfolio can spread the risk of climate change, provide flexibility for urban water systems to be more adaptive, or both. Diversity can mean developing climate-independent sources of supply alongside traditional supplies, having a variety of sources of supply spread geographically or across scales, having a range of supply-side and demand-side options, or any combination of those measures. Portfolio diversity, of various types, will be seen as valuable in both climate change resistant and climate change resilient stances in urban water planning.

Diversity on the supply side

It is generally recognised that there is a need to diversify the sources of water supply for our cities in the face of climate change. This can be seen as a need to move away from total reliance on a single or a few climate-dependent sources of water supply, particularly rivers or dams. As Erlanger and Neal (2005) noted, having a diversity of sources will reduce risks compared to relying on a single supply. Diversifying supplies can be seen as tapping sources in various catchments, particularly if those catchments are subject to varying rainfall and climate influences.

A common approach to diversifying supplies includes tapping groundwater and desalinated seawater as well as new surface water sources. In the future, indirect potable water recycling could also play a role in some regions. These sources all have differing risk profiles that together reduce the combined risk of the portfolio. They also have the major advantage of being totally or partly climate independent, thus improving water systems' resistance to climate change as well as increasing the diversity of sources. Moves to diversify supplies by introducing a climate-independent source are evident in the five largest Australian cities: Melbourne, Sydney, Brisbane, Perth and Adelaide are all developing desalination.

Diversity on the demand side

As well as diversity in the location and type of large-scale supply, from a climate change resilient stance at least, portfolio diversity is also promoted through having a range of smaller scale supplies in urban areas, through non-potable supplies, and through water utilities pursuing a suite of water efficiency measures.

In IRP, small-scale and alternative supplies are usually both considered for analysis purposes to be on the 'demand side', as they are measures that reduce demand on centralised potable supplies. Alternative water supplies include residential rainwater tanks, rainwater collection from large commercial roofs and local council stormwater harvesting schemes, as well as non-potable wastewater reuse at various scales. In coastal areas, localised rain-fed sources often have the advantage of different patterns of rainfall when compared to large surface water sources with inland catchments. In the same way, residential greywater systems, small-scale wastewater reuse (commonly based on sewer mining) and large-scale non-potable recycling schemes provide alternative sources of supply and an increase in diversity.

Smaller scale options such as rainwater tanks and reuse systems can provide a further step in diversifying urban water systems by diversifying ownership and control. Policies at the state and federal levels in Australia are currently geared to promoting such small-scale and alternative supplies (for example, in new developments through planning regulations and green building accreditation and in existing areas through stormwater grants and greywater and rainwater tank rebate schemes). The result of these government policies is to encourage the development of a wide range of supplies at varying scales, owned by a variety of entities. Policies that result in the widescale take-up of a range of small-scale distributed water supplies will certainly increase the resilience of urban water systems. However, further work is needed to determine how these policies should be assessed and managed as part of the full portfolio of supply and demand options.

Demand-side diversity is also achieved by governments and water utilities developing water efficiency measures that target a wide range of end-uses as part of the supply–demand mix. This involves considering the conservation potential of the various non-residential end-uses by sector and subsector, as well as all major household end-uses (showers, clothes washers, toilets, taps, dishwashers and outdoor water use). In inland centres, water demand can be highly skewed to summer demand because of the large volumes of water used for outdoor irrigation and evaporative cooling. In those regions, in particular, demand-side diversity should involve targeting such seasonal end-uses.

Water efficiency measures provide both GHG mitigation and climate change adaptation. From a mitigation perspective, water efficiency can substantially reduce energy use and GHG emissions. As discussed in Section 4.5.1, energy is saved through avoiding water and wastewater transport and treatment and to a greater degree through avoiding the need for water heating by customers.

Water efficiency measures provide benefits for climate change adaptation by decreasing the overall water demand in a region and thereby increasing the buffer capacity between supply and demand for that area. Increased water-use efficiency can also be expected to reduce the minimum levels of supply that a community would require during a period of intense supply shortage, such as during extreme drought. Indoor plumbing products (showerheads, taps, toilets, urinals etc.) and indoor appliances (such as clothes washers and dishwashers) are of particular importance at those times, because water use in such fixtures is to a large degree non-discretionary and the volumes used will depend on the technical efficiency of the product. For example, toilet flush volume will be a limiting fact for a household's ability to minimise water use, and measures that increase toilet efficiency can reduce that limitation. Finally, water efficiency can also be a drought response measure if it is rolled out through an accelerated demand-management program (see 'Readiness options' in Section 4.5.3).

Because of the range of mitigation and adaptation benefits, responding to climate change should see an enlarged role for water efficiency in supply–demand planning.

Assessing portfolio diversity

Taking a portfolio perspective provides a means of assessing the benefits of a diversity of water sources and the benefits of demand-side options alongside supply-side options. It involves assessing options according to how they will affect the characteristics of the whole portfolio: options are considered in terms of what they add to the group, rather than in isolation.

Different combinations of options have different implications for an urban water system's vulnerability to climate change and, more specifically, its vulnerability to drought. Also, different combinations of options provide different levels of flexibility. That flexibility might arise because the options can provide additional yield for a period (for example, some groundwater sources can be 'overdrawn' for a period). Alternatively, water might come from a range of different sources at a range of scales, reducing reliance on a single source (for example, new developments with household rainwater tanks, development-scale recycled water and potable supply).

Quantitative analysis of portfolio characteristics, such as decreasing climate change vulnerability and increasing flexibility, has been developed to some extent. Wolff (2008) describes a risk-based method for calculating option cost-effectiveness based on a 'constant-reliability' unit cost. This method values the contribution of options in terms of the volume supplied or saved from an option during drought. This is in contrast to unit cost calculations based on the average annual yield supplied by an option, as is standard practice in IRP. The method accounts for the fact that some options are more reliable in their supply or savings than others, and also that options will vary in whether their yield is positively or negatively correlated to the existing system yield during drought. Wolf (2008) states that the method presented is a strong starting point for quantitative analysis of the cost implications of uncertainty in supply- and demand-side options. The importance of assessment on a portfolio basis rather than on an individual option basis is highlighted. However, the need for data to describe statistical distributions may hinder the method's application in practice.

A portfolio-based assessment of options can also be qualitative. One approach would be to include portfolio performance criteria into a multi-criteria analysis. Options could then be rated on whether they are likely to improve the portfolio's overall performance on the set of selected criteria. Possible criteria include:

- decreases the *vulnerability* of the portfolio to climate change impacts
- increases the *diversity* of supply sources
- increases the *diversity* of end-uses targeted by demand-side options
- increases the portfolio *flexibility* to deal with future uncertainties.

The application of multi-criteria analysis as part of IRP is described in *Sustainability assessment in urban water integrated resource planning* (Fane et al. 2010, in this document). A portfolio perspective can also align with moves towards more adaptive planning—the portfolio can be incrementally adjusted and readjusted as the future unfolds and situations are reassessed.

4.5.3 Developing adaptive measures

Probably the most significant implications of climate change for urban water supply–demand planning stem from uncertainty about future climate. For many regions, water planning will be conducted without strong confidence in projected climate parameters and with the potential for increased climate variability into the future.

In such a context of climate uncertainty, moves towards adaptive planning can be expected. In some locations, this will mean that drought response planning and contingency measures may come to the fore. In other regions, moves towards adaptive planning will go one step further and include 'readiness options' as part of 'readiness strategies'. Assessment methods such as real options analysis can be used to assess adaptive measures.

Drought planning

In supply–demand planning for urban water in Australia, managing with climate uncertainty is to a significant degree about managing with drought. Drought response and contingency planning have always been critical components of supply–demand planning. However, as discussed in Section 4.2.1, for some regions climate change is likely to interact with natural climate variability, resulting in more frequent and more severe droughts.

In Australia, planning for drought has always been an important aspect of urban water supply–demand planning. As well as a long-term plan to balance supply and demand, water utilities should have a drought response plan and a contingency or emergency plan (Erlanger and Neal 2005). When droughts occur, the drought response plan traditionally provides a short-term response in the form of water restrictions. In case of an extreme drought, a contingency plan with emergency measures is needed to ensure that basic water needs for the community can be met through the provision of a minimum level of supply at all times.

Drought planning incorporates predetermined triggers, based on the level of storage in the existing system, for water restrictions and then for emergency measures. Where these trigger levels are set is a critical determinant of system yield. To date, the connections between drought response plans, contingency plans and long-term supply–demand planning have been consided predominantly in terms of these supply-side implications.

The expected increases in climate variability in many regions mean that it is likely there will be a greater role for measures that are triggered during drought. As adaptive approaches are developed to manage urban water supply in the context of climate change, it is highly likely that long-term supply–demand planning and drought planning will become much more integrated.

Readiness options

Readiness options expand the idea of contingency measures beyond emergency situations to include options that are preplanned and triggered at a predetermined point during a drought. Readiness options can be supply- or demand-side options and ideally can be mobilised quickly when required. They are developed to provide a capacity to respond to a water shortage but are not implemented until predefined trigger levels are reached. Sources that have the potential to be used as readiness options include:

- new or existing groundwater bores
- new desalination capacity
- intercatchment transfer pipelines or the activation of existing transfer potentials
- indirect potable recycling.

Readiness options provide some flexibility in timing and also, potentially, in the scale of implementation.

Similarly to water restrictions in a traditional drought plan, readiness options are characterised by trigger points based on storage levels or supply allocations for the existing supply system. The trigger points reflect the lead-time for bringing particular water sources online. Developing a readiness option involves preparation as well as preplanning. This can include pilot plants, detailed design, approvals, site preparation and other relatively long lead-time but low-cost elements of implementation.

The more preplanning and preparation work that can be done in developing a readiness option, the longer the critical storage-level trigger for construction can be delayed. This provides a significant benefit because delaying implementation means that a readiness option may not need to be triggered before a drought breaks. A major financial cost can then be avoided until it is needed at some future point.

Large-scale accelerated demand-management programs also have the potential to be implemented relatively quickly during drought. Examples of demand-management measures that have been implemented on a large scale in response to water shortages include:

- showerhead exchange programs

- residential household audits and retrofits
- rainwater tank and washing machine rebates
- enhanced leakage programs
- enhanced non-residential audit and conservation programs.

Large-scale demand-management options do not usually involve large irreversible capital investment. However, unlike other readiness options, they cannot be discontinued when they are no longer required. Nevertheless, many can be considered as ‘no regrets’ or ‘few regrets’ options because water savings benefits will persist into the future and their unit costs are less than, or not significantly greater than, the marginal cost of supply. Even with readiness supply options such as desalination, in many cases it is likely that they will not be switched off once a drought breaks, but an adaptive approach will see them incorporated into the longer term supply–demand balance.

By staging readiness options, readiness strategies can be developed, first with ‘no regrets’ accelerated demand management and followed by lower cost contingency measures such as new groundwater bores. These types of measure buy time during a drought and delay the arrival of critical storage trigger levels for the construction of more expensive supply, such as desalination or potable recycling. The use of adaptive measures in a readiness strategy reflects a desire to refrain from large capital investments during the current environment of climate change uncertainty, while also recognising that total water supply system failure is catastrophic and must be avoided.

4.5.4 Assessing adaptive measures

‘Real options’ analysis is a risk-based method for assessing strategies or the alternative decision paths of an adaptive approach. The method factors the probability of future outcomes into an assessment that compares strategies on their risk-weighted costs. The method is drawn from the financial management sector, and variations on it exist. A detailed explanation of one real options methodology and an example application in urban water planning are given in Borison and Hamm (2008).

Real options analysis is designed so that, as new data emerges over time, learning can occur and the new information can be incorporated into the analysis. New information can influence the choice about which strategy or decision path should be followed. Applied in urban water supply–demand planning, real options analysis has the potential to be used to develop risk-weighted cost comparisons of readiness strategies. It can also be used to compare these more flexible strategies to strategies that aim to provide drought security based on building additional supply capacity in the near term, before drought occurs.

As with other quantitative risk-based analyses, real options analysis is characterised by a need for data on, or assumptions about, the probability that particular future outcomes will occur. In urban water planning, the uncertainties most easily accounted for will be decision path uncertainty (the decision path is the likely sequence of decisions made in response to situations in the future) and financial uncertainties associated with the costs of options. In some locations, historical records may be able to provide climate and hydrological variable probabilities. However, in many regions the uncertainties associated with climate and hydrology may be difficult to determine. A possible analytical approach for dealing with climate uncertainty would then be to combine real options analysis with scenarios analysis based on a range of climate change scenarios.

Whether as part of real options analysis or a separate piece of analysis, ‘drawdown’ curves are likely to be an important piece of analysis for any region considering a readiness strategy. Drawdown curves show the number of years or months that the region’s storages and other sources can continue to supply a restricted water demand under the worst case scenario. The worst case scenarios need to account for historical droughts as well as climate change (see Section 4.4.2). Such curves will commonly start from existing supply levels and illustrate how long a restricted demand could be drawn under worst case conditions. Because the worst case scenario will determine the trigger levels for the readiness strategy, it needs to represent a ‘reasonable’ worst case estimate. What that is can only be judged on a region-by-region basis.

Significantly, the length of time available for a readiness strategy, as illustrated by drawdown curves, will vary between regions. It will be critically influenced by the size of the available storages, as well as the worst case scenario selected. For example, in high-rainfall regions where storages are typically smaller, the drawdown under a worst case scenario will be relatively fast, perhaps over a year or less. In low-rainfall areas with relatively larger storages, the drawdown will take multiple years if it starts from full storages.

Even if quantitative analysis is considered unfeasible, real options principles can be applied to water planning in the face of climate uncertainty. Those principles include:

- recognising the importance of delaying large irreversible investments as long as possible
- promoting flexibility through the explicit definition of a range of decision paths that can be taken into the future
- designing options (such as desalination, groundwater and indirect potable recycling) so that they are modular and might therefore be staged
- learning from new information as it emerges.

4.6 Monitoring, evaluation and review

Step 5 of the IRP framework involves monitoring, evaluation and review. In the *Guide to demand management and integrated resource planning for urban water* (Turner et al. 2010), this covers:

- the monitoring and evaluation of individual demand-management measures
- the monitoring and evaluation of the suite of options in relation to the planning objectives
- the review of the whole IRP process.

Climate change and climate uncertainty increase the range of parameters that need to be regularly monitored and evaluated by water utilities and water planners. In the context of climate change, many water utilities have already started monitoring the energy and GHG emissions implications of their water supplies and demand-management programs. Adaptive approaches to managing climate uncertainty require a wide and ongoing monitoring of key climate and hydrological variables, as well as constant monitoring of the conditions of the existing system. Even in locations where a more climate change resistant approach has been taken to planning, enhanced monitoring should be targeted at key areas of known uncertainty, such as how supply catchments are responding to changes in rainfall and temperature patterns. With significant levels of uncertainty in some areas and our knowledge about climate change rapidly evolving, there is also a need for regular review of supply–demand planning processes in all regions.

This section first addresses the monitoring and evaluation of energy and GHGs. It then discusses monitoring and evaluation as part of an adaptive approach to managing climate uncertainty. Finally, it considers the climate change implications for the ongoing review of supply–demand plans and planning processes.

4.6.1 Monitoring and evaluation of energy and GHGs

Monitoring and reporting on the energy use and GHG emissions associated with water supply are a critical step in mitigating of the impacts of climate change by reducing GHG emissions. The energy use of infrastructure across the urban water system should be measured and evaluated. This includes pumping stations, desalination plants, water recycling facilities and household rainwater tanks. The energy use of that infrastructure can be measured directly or as part of a monitoring and evaluation study (for example, for rainwater tanks). Similarly, the direct GHG emissions from infrastructure such as recycled water plants and new dams also need to be monitored.

As discussed in Section 4.5.3, demand-management measures can be expected to result in a net reduction in energy use. This is due to the reduced energy use associated with water supply, wastewater treatment and customer water heating. *Techniques for estimating water* *saved through demand management and restrictions* (Fyfe et al. 2010, in this document) addresses the methods for evaluating of water and energy savings from demand-management programs.

4.6.2 Monitoring and evaluation in managing climate uncertainty

Monitoring and evaluation become increasingly important in the context of climate uncertainty. Adaptive management is premised on responding to information about the current situation as it emerges. The monitoring and evaluation process develops that information.

For example, ongoing monitoring of both current water demand and available supply (dam levels and inflows or river or groundwater levels) is needed to develop a picture of the current situation. However, supply and demand data can only be evaluated in the context of the seasonal outlook and an understanding of historical water demand and supply trends. This, together with information on the level of preplanning and preparedness of readiness options, is necessary to inform alternative decision paths.

Monitoring and evaluation can also be targeted at areas of known uncertainty, such as the relationship between rainfall intensity and runoff and seasonal influence on catchment responses. Soil moisture changes are expected in some catchments because of changed seasonal rainfall and evapotranspiration patterns, and this could result in drier catchments and substantially less runoff generation due to non-linear rainfall–runoff responses. These types of effects may be both context- and time-dependent. Hence, a case can be made for collecting more rainfall, runoff, temperature and evaporation data in catchments to better understand catchment drying. This includes the rainfall–runoff effects in specific regions and how system yields will be affected. As part of adaptive management, the additional monitoring data will be fed back into water planning and also inform an unfolding understanding of future climate.

4.6.3 Ongoing review of the supply–demand plan and the IRP process

Knowledge about climate change at global, national and regional levels is evolving relatively quickly, and new knowledge (for example, new regional climate change downscaling studies) can alter the context of water supply–demand planning for a given urban area. Frequent reviews of supply–demand plans will be necessary.

Furthermore, there is a need for ongoing review of how the IRP process is being applied in each regional context and at the state government or Australian Government policy level. Both reviews will be in the context of our evolving understanding of climate change and its impact on water resources and water demand.

4.7 Conclusions

The principal message of this paper is that the impact of climate change on both supply and demand needs to be accounted for and should be integrated into urban water supply–demand planning.

Four additional core messages should be taken from this paper:

- The mitigation of GHGs needs to be a parallel objective to climate change adaptation in urban water supply–demand planning.
- Demand-management programs that increase water-use efficiency help to meet both climate change mitigation and adaptation objectives.
- The best estimate of expected climate change should be included in calculations of the longer term supply–demand balance, as well as in yield estimates for new climate-dependent options.

- Knowledge of climate science is evolving, and there is a significant amount of uncertainty in the current knowledge. However, the uncertainty about future climate due to climate change can be managed either by strategies aimed at decreasing vulnerability to climate change or by both decreasing vulnerability and increasing the adaptive capacity of urban water systems.

In relation to the mitigation of GHGs, the key points raised in the paper are as follows:

- Energy use in water supply has historically been low. New water sources, however, tend to be more energy intensive, so the energy intensity of water supplies is rapidly increasing.
- Surface emissions from water storage are highly uncertain but could be an important GHG source. While little can be done about existing storages, because reservoir surface emissions may be so significant it is critical that they are fully assessed for any new water supply dams proposed in Australia.
- The positive and negative GHG implications of all supply- and demand-side options, not just energy-intensive new supplies, need to be accounted for in options analysis.
- Helping to reduce customer water-heating energy consumption through demand-management programs targeting hot water usage can have a large mitigation outcome. However, such actions should not be viewed as an alternative to addressing the energy used in the provision of water services.

On the role of water-use efficiency, the main points made in paper are:

- demand-management programs that promote increased water-use efficiency will reduce the energy intensity of water service provision
- by decreasing overall water demand through water-use efficiency, the buffer between water demand and supply is increased
- increases in indoor water-use efficiency can be expected to reduce the minimum levels of supply that a community would require during extreme drought
- accelerated demand-management programs can be considered as a drought response measure as part of readiness strategies.

In relation to including the best estimate of expected climate change in the analyses, the main points made in the paper are as follows:

- Various approaches exist for generating climate change scenarios for use in urban water planning. The most rigorous and, in Australia, the most widely accepted is to base climate change scenarios on GCM simulations, with the global climate projections 'downscaled' to a regional level.
- Climate change is expected to affect both sides of the supply–demand balance. The impacts on demand are likely to be small compared to the impact on supply in most regions.
- Both the supply and demand forecasts used to establish the base-case supply–demand balance and those in yield estimates for new climate-dependent options should incorporate 'best estimates' for climate change in a region.
- The high and low scenarios should also be considered in order to represent wet and dry extremes for future climate.

On the subject of managing climate uncertainty, the main points the paper makes are as follows:

- To manage uncertainty about future climate due to climate change, strategies can be aimed at either decreasing vulnerability to climate change (taking a 'climate change resistant' stance) or both decreasing vulnerability and increasing the adaptive capacity of the urban water systems (taking a 'climate change resilient' stance).

- A move towards more adaptive planning requires adaptive management; the development of adaptive measures; increased monitoring and evaluation and more regular review of supply–demand plans; consideration of short planning periods; better integration of short-term (drought) and long-term planning; and a reconsideration of governance in the light of more adaptive planning.
- Important questions remain about managing climate uncertainty, including 'What represents a 'reasonable' worst case climate change scenario?' and 'How can we assess whether a portfolio of options represents the most cost-effective and sustainable means of providing resilience (or resistance) in the face of climate change?'

4.8 Key resources

4.8.1 Climate change assessments across Australia

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5. Techniques for estimating water saved through demand management and restrictions

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Summary

What is the purpose of this paper?

A key aim of the Australian integrated resource planning (IRP) framework *Guide to demand management and integrated resource planning for urban water* (Turner et al. 2010) is to ensure that water service providers embed monitoring and evaluation (M&E) into the water planning and implementation cycle. Water efficiency programs, regulations, restrictions and other demand-management initiatives typically provide an extremely cost-effective means of minimising the supply–demand gap by reducing short- and/or long-term potable water demand. Indeed, in some locations across Australia specific demand-management targets have been set to capture such savings. However, while some water utilities routinely undertake internal evaluations of their programs, only a handful of such studies have been published, and the analysis techniques involved remain largely inaccessible to the broader industry (Turner et al. 2007).

Turner et al. (2010) discuss the key dimensions of M&E, including the importance of measuring participation rates and customer satisfaction for specific implemented programs and comparing the anticipated outcomes. Turner et al. (2010) also provide guidance on determining cost-effectiveness, thus assisting water service providers to modify and improve programs where necessary. This resource paper deals with quantifying the water savings achieved in demand-management programs, similarly assisting water service providers to improve programs, but also enabling them to determine whether they have achieved their desired goal or target in reducing water demand in a cost-effective way.

Why is the paper needed?

Although there has been significant investment in demand management in Australia, there appears to be very little evidence of robust evaluation of the savings achieved. This paper therefore seeks to provide existing and potential users of the Australian IRP framework and the *Guide to demand management and integrated resource planning for urban water* with a broader understanding of the various analytical techniques that can be used depending on data availability. It also draws together some of the limited examples currently available and provides a case study documenting the application of two different analytical techniques in the evaluation of water savings from a residential water-efficiency program.

Will this paper be useful to me?

The resources developed as part of the National Water Commission's Integrated Resource Planning for Urban Water project are intended to assist individuals in the water industry who are focused on urban water planning and management. That audience is very broad, ranging from large water utilities dealing with large investments to small councils potentially with limited resources, skills or both. The resources developed as part of this project aim to focus on the core group of organisations and practitioners in the middle of that spectrum.

Hence, the intended audience for this resource paper is those individuals and teams responsible for water service provision and management who are involved in or need to be

involved in monitoring the outcomes of implemented demand-management programs. Members of that group will have varying knowledge and skills, so this paper aims to provide both a broader and a deeper perspective on techniques available and how they can be useful. Many individuals and teams responsible for the M&E of implemented demand-management programs may contract out all or part of the work in their region. Therefore, this paper also aims to provide sufficient background on the various available techniques for practitioners to engage more effectively with the package of contracted work and the resulting output.

Where to look in the paper?

This resource paper contains eight main sections in addition to this summary:

- Section 5.1 provides an overview of the current challenges in M&E of demand-management programs and identifies some of the key techniques available.
- Section 5.2 examines the kinds of data needed for the various analytical techniques.
- Section 5.3 provides guidance on data processing, which is a critical component and often requires a significant proportion of the resources needed when undertaking M&E.
- Section 5.4 outlines the array of techniques available.
- Section 5.5 covers evaluating savings from water restrictions.
- Section 5.6 highlights the general pitfalls and limitations of the various techniques described.
- Section 5.7 provides some examples in which the identified techniques have been used.
- Section 5.8 provides a case study example using one of the most robust and replicable techniques available and a new emerging technique, and compares savings results obtained using the two different techniques.
- Section 5.9 contains a summary of useful references on this topic.

Scope of this resource paper

Monitoring and evaluation (M&E) covers many dimensions. This paper aims specifically to outline the various analytical techniques that can be used to measure water savings when implementing demand-management (DM) programs. It also draws together some of the limited examples currently available and provides a case study documenting the application of two different analytical techniques used to measure water savings from a residential water-efficiency program. Other dimensions of M&E associated with the need to assess participation rates, customer satisfaction, savings from non-residential programs and cost-effectiveness are covered to varying extents in Turner et al. (2010).

What are the take-home messages?

Even with significant expenditure on demand-management programs in recent years, there is little evidence of M&E of implemented programs, and when M&E are conducted the techniques used are often flawed, providing misleading results. This paper is designed to aid practitioners in understanding the techniques available and what kind of data and data processing are needed, and to provide examples and a case study of how various techniques have been used. This resource will enable water service providers implementing programs to embark on M&E of their programs with a greater level of confidence and understanding of what is entailed.

5.1 Introduction

5.1.1 The increasing role of demand management and restrictions

Demand-reduction initiatives provide a relatively inexpensive means of closing the supply–demand gap by providing short- and/or long-term potable water savings. The term ‘demand management' is typically applied to water efficiency programs and regulations that effectively and permanently reduce demand. Alternative forms of supply, such as rainwater tanks and permanent water conservation rules, are also considered to be forms of demand management. Determining the impact of demand management is critical for establishing the efficacy of such measures as well as their costs, to enable comparisons with other options for closing the supply–demand gap.

In recent years, a broad spectrum of measures have been used to play a critical role in many water management plans across the country, from emergency drought response through to long-term supply–demand planning. Such measures include:

- short-term restrictions mainly affecting outdoor garden watering
- medium-term water efficiency programs affecting both indoor and outdoor structures (for example, the fitting of efficient showerheads) and behavioural demand (such as having shorter showers)
- long-term regulations forcing new and existing households to meet significant demand-reduction targets (for example, through the 40% reduction target for water consumption in new dwellings as part of BASIX in New South Wales).

Water restrictions are temporary measures used to achieve short-term reductions in water demand to ease pressure on supply during drought and other supply-constrained periods. They are considered supply-side options because they influence the yield (see Step 3b in Turner et al. (2010). Accordingly, they are not classified as demand-management initiatives or considered on the demand side in the IRP process. Nonetheless, their impact is often subject to evaluation both to gauge their effectiveness and to allow for corrections in evaluations of other demand-reduction measures.

5.1.2 The importance of evaluation

Despite significant investment in such initiatives, there has been relatively little evaluation of the actual water savings achieved after implementation ('ex-post' assessment). Quantifying the savings arising from demand management is essential. In the IRP process it helps to ensure that demand-reduction targets, which use estimated savings based on theoretical savings or results borrowed from other areas—that is, predictions of savings ('ex-ante')—are being met. In regions actively involved in demand management, evaluation assists in determining whether demand forecasts remain reliable over time. It also ensures that investment in demand management is cost-effective by informing decisions on how to take actions to improve the effectiveness of initiatives being implemented (Turner et al. 2007).

5.1.3 Techniques available

This paper describes the various statistical evaluation techniques that may be used to measure the savings from demand-reduction measures after implementation (ex-post). The techniques discussed in Section 5.4 can be used (and in some cases have been used) to measure savings from demand-management initiatives, such as residential:

- education programs
- indoor retrofit programs
- showerhead swap rebates
- washing machine rebates
- toilet retrofits
- outdoor garden tune-ups
- garden equipment and baskets of goods rebates
- rainwater tank and greywater system rebates
- household leak repair programs
- pressure-reduction programs affecting the customer side of the meter.

Techniques for estimating savings from water restrictions are addressed in Section 5.5. Techniques used to measure the savings associated with the non-residential sector are not covered by this paper.

The kinds of techniques used include:

- basic before–after tests
- various participant–control means comparison methods
- regression analyses, including time-series, covariate, cross-sectional and panel data regression.

When using each of these methods, it is critical to take into consideration various potential limiting factors, such as:

- the kind of data available (for example, bulk water production data, customer meter readings, intervention records and climate data, and whether additional demographic, end-use or behaviour survey data is available)
- the quality of the data, the duration (for example, three-, four- or six-month reads for customer meter readings), the period available before and/or after the intervention, and data processing limitations, including linkages to multiple databases
- the size of the sample or samples available
- the time, resources, skills and expertise available to do the analysis
- complicating factors (such as price changes, restrictions and multiple water efficiency programs acting in parallel), which may make it more difficult to tease out the effects of a specific program of interest.

The various techniques, types of data available, skills of the analysts and complicating factors all need to be considered before undertaking any M&E exercise. Indeed, before even embarking on the implementation of any demand-management initiative it is best to clearly identify what data needs to be collated, how and in what format, so that the M&E process is streamlined. Many evaluations are compromised because these issues were not considered early in the process, often limiting the techniques that can be used and the clearness with which savings can be discerned.

It is also important to understand why the M&E exercise is being carried out. For example, is it to quickly check the level of estimated savings at the earliest possible moment for a pilot of the program when data and/or sample size allows, to reassure decision makers that the program should be implemented? Or is the M&E part of an ongoing program that attempts to tease out the savings of individual programs that are being affected by restrictions, and any potential decay in savings? Again, the technique used will depend on why the evaluation is being conducted and the level of certainty and detail about savings that is required.

A wide array of analytical techniques can be employed to measure savings. This paper describes a number of techniques reported in published documents. There are likely to be many more variations, hybrids and alternatives that can be adopted, depending on the objectives and circumstances of the evaluation task at hand. The evaluation technique adopted should be devised and tailored to suit the level of accuracy required and the expertise, resources and data available. Generally, the greater the accuracy sought, the higher are demands on time, cost and knowledge. Data is often a limiting factor in devising a methodology, and the type, detail, quantity and quality of data available are all considerations.

It should be noted that data processing is often the most time-intensive stage of the evaluation process, as reliable data is critical to avoiding misinterpretation of results. A number of the techniques described in this paper involve complex data manipulation and analysis, which may be beyond the capacity of smaller water service providers. Hence, this paper is also useful as a guide to specifying, understanding and/or verifying evaluation studies performed by external consultants.

5.2 Data needs

The type of data required to evaluate water savings associated with demand-reduction programs depends upon the estimation technique. However, all empirical methods require, at a minimum, some form of customer meter demand data (CMDD) or bulk water production data (BWPD), as well as markers of the program commencement date and details of the interventions undertaken. Where a program affects individual users at different times, the commencement date is preferably broken down into individual intervention dates. Other data used in empirical analyses may include household characteristics (household size, income, appliance ownership, dwelling type etc.), local demographic data, meteorological data (for example, rainfall and temperature), and data on other influential external factors such as rollouts of other demand-reduction initiatives (particularly water restrictions) and changes to water pricing and regulation.

5.2.1 Water demand

The primary data used in empirical evaluation methods is BWPD or CMDD. Assessments of the impacts of water restrictions frequently utilise BWPD, as it is often easier to obtain and process and is normally available at a daily time step. Evaluation of residential water efficiency programs generally requires at least CMDD from participant water users, before and after program implementation. More rigorous methods tend to incorporate consumption data from customers not participating in the program of interest, which acts as a ‘control’ or ‘comparison’ set. It may also be possible to use BWPD to evaluate residential water-efficiency programs. However, this is only viable where the data can be (largely) isolated to the residential sector. Where that is impossible, the analysis is less likely to produce reliable savings estimates because there is reduced scope to control for concurrent demand-reduction measures and the data is subject to the influence of non-revenue water and system leaks.

The length of the time series of BWPD or CMDD required depends on the method used to evaluate water savings. Around 12 months both before and after the program takes effect is a suggested minimum requirement, to determine potential seasonality in water savings. However, a longer time series is typically required, specifically where single years are atypical in terms of climate or other anomalies, which may produce non-representative water usage patterns. This is particularly the case for regression techniques, especially those based on climatic variables. A longer time series of consumption data after program implementation is also desirable, to be certain of potential seasonality in water savings, to determine whether savings are consistent in the longer term, and/or to detect decay in savings over time.

5.2.2 Program commencement and intervention dates

The effects of demand reduction are almost always measured using a ‘before and after’ comparison. When gauging the effect of restrictions, obviously the timing of the introduction of different stages of restrictions is critical. For water efficiency programs, the implementation occurs at a customer level and thus tends to occur on a rolling or sporadic basis over an extended period (rarely would a program engage all participants in one day, week or month). Therefore, evaluation of such programs tends to require data on when the program intervention occurred for each individual participant, details of the interventions undertaken in each property and the overall program commencement date. In a retrofit program, the intervention date might simply be the date of the retrofit visit in which water-saving fixtures and fittings were installed. The intervention date under a rebate program, however, may be less well-defined, as it could be indicated by the date the rebate was applied for or when it was paid. In rebate schemes that depend on the participant to install the product (such as showerhead programs), recorded dates may bear no relation to the date of the installation because the participant may take some time to install the device. Education or behaviour change programs may involve multiple interventions, in which case discretion is required in choosing how best to interpret intervention dates in the analysis. When multiple conservation programs have been initiated, intervention dates for each program are required in order to effectively isolate water savings from each program.

In general, program intervention information will be located in a different database from the CMDD. As a result, the two data sources need to be linked for analysis. This process requires a common property identifier in both databases and can be complex when manipulating large datasets.

5.2.3 Program details

When evaluating large programs with multiple potential interventions, it is essential to collate and store accurate data on the actions taken for each household to assist in evaluating the effectiveness of savings from each component of the program being implemented. This enables the program to be assessed and reviewed, and any program component that does not appear to be contributing sufficiently to savings can be deleted or modified accordingly. Programs such as the original Sydney Water Every Drop Counts Residential Retrofit Program (now called ‘WaterFix’), have various components, including installation of an efficient 3-star showerhead, tap flow regulators on kitchen and bathroom taps and a toilet cistern weight, as well as advisory services on efficiency tips and tricks around the home. This program, which has been implemented in Sydney for over 10 years in more than 500 000 households, has benefited from careful data collation of individual household modifications, enabling detailed and ongoing evaluation (Turner et al. 2005).

5.2.4 Dwelling type

The dwelling type is a fundamental consideration for evaluations of residential water efficiency programs. Most of the techniques described are best applied to individually metered properties, which in most cases tend to be single detached dwellings, as water savings are not diluted by the influence of other non-participant properties attached to the same water meter. As the number of individually metered multiresidential properties grows (due to changing building codes and other regulations that mandate submetering), so does the feasibility of evaluating water savings from the multiresidential sector. However, where individually metered multiresidential properties are not common, it is generally advisable to limit analyses to single detached dwellings in order to more clearly isolate the savings of the intervention.

5.2.5 Household characteristics and demographic data

A wide range of household variables, demographic data, or both may also be used to enhance the definition and richness of an empirical analysis of water savings. These might include:

- local government area or other geographical grouping

- household size
- age and/or condition of the house
- property value
- lot size
- household income
- age of the occupants
- number and type of water-using appliances and plumbing fixtures
- pool/spa ownership
- other characteristics, such as whether the household includes a home business.

Depending on the nature of the analysis, this data may be required at an individual or aggregate (for example, suburb or statistical district) level. The main limitations associated with the use of household characteristic and demographic data are the high cost of its collection and the added complexity it brings to the analysis. Demographic data from the Australian Bureau of Statistics (ABS) can be readily linked to consumption data by geographical area to inform cross-sectional and panel data regression analyses (see Section 5.4.3). However, when more detailed household data is sought, some form of survey is usually required, which tends to limit the reach and sample size of the evaluation and thereby compromises the statistical significance of the results. Hence, a balance must be found between limiting sample size and maximising statistical power.

5.2.6 Meterological data

Climate is one of the most influential factors on water demand because it dictates consumption through some of the more water-intensive end-uses, including irrigation, evaporative cooling and pool filling. Accordingly, the effects of season and weather must be accounted for in an evaluation of water savings, either in the interpretation of the results or by incorporating those effects into the analysis. At the time resolution typically considered in evaluations of demand-reduction initiatives, the influence of seasonal variation is of most concern, so a basic tenet of savings estimation is to compare demand figures only from like months. A number of the techniques described in this paper also make use of a control group to account for the effects of both climate and weather, including two-way analysis of variance, matched pairs means comparison or covariate regression. Other forms of regression analyses may incorporate dummy variables or Fourier series variables to explain seasonal variability (see Fyfe et al. 2010).

However, when a finer explanation of seasonal and weather effects is required, meteorological data may be directly factored into a regression model. Most commonly, temperature, rainfall and evaporation data is used as variables in regression models. This data is relatively easy to obtain from the Bureau of Meteorology (BoM) at a small cost. Often, however, it contains numerous missing or poor-quality entries, which must be dealt with in the processing. Alternatively, patched point and data drill datasets may be purchased from SILO.[1] Patched point data provides long-term BoM station records that have been ‘patched’ by infilling missing data with interpolated values. Data drills, on the other hand, provide complete long-term records of a comprehensive range of meteorological parameters for any point on a five-kilometre grid across Australia, based on the spatial interpolation of BoM records and some synthetic data.

[1] Part of the Australian Bureau of Meteorology, http://www.longpaddock.qld.gov.au/silo (accessed 31 March 2010).

5.2.7 External factors

Finally, broadscale external factors that could influence demand, but which are not part of the demand-reduction measure being assessed, may also be factored into savings evaluations. These might include changes to water policies and regulations, price, public awareness campaigns, changes to water restrictions (even when they are not the focus of the analysis), the introduction of alternative water sources and the rollout of other demand-management programs.

At a minimum, dates when the changes or introductions occurred are required. Information on the nature of the factor in play is often necessary to further unpack its effect on water demand and on water savings from the demand-management program of interest.

Water restrictions are most likely to interfere with savings estimates for outdoor demand-management measures, as they directly influence outdoor demand. However, they can also influence evaluations of indoor programs both directly, by reducing indoor demand, and indirectly, by exaggerating or diminishing changes in demand associated with an indoor program. Information on which activities are restricted and at what times helps to interpret the intricacies of the effects of restrictions on demand and, when regression analysis is used, determines how to specify corresponding explanatory variables.

Building codes are the main form of regulation that will influence water usage, and many states have adopted new standards that mandate water-efficient fixtures and fittings in new and renovated dwellings. When a participant–control or matched pairs means comparison method is adopted for the savings analysis (see Section 5.4.2), households that were subject to such codes should be excluded from the analysis. The national Water Efficiency Labelling and Standards (WELS) Scheme will also have influenced purchases of water fixtures and appliances in many households, and consideration should be given to how that may affect the analysis. However, like the effect of public awareness campaigns, the effect of WELS is difficult to gauge, so a discussion on its likely effect on the analysis may be the only option.

Price should only be a significant factor when the tariff or its structure has undergone a significant adjustment that would elicit a discernible response from consumers (for example, the introduction of a new block tariff structure or large changes to intramarginal rates). Accommodating the effect of such adjustments can be as simple as utilising a dummy variable in a regression; however, the complexity of price effects sometimes warrants close attention and the reader is advised to consult *Complementary analytical techniques for urban water forecasting in IRP* (Fyfe et al. 2010, Chapter 3 in this document) for guidance.

Alternative water sources such as bores or rainwater tanks can potentially have a large bearing on the outcome of a water savings analysis. At the very least, an attempt should be made to collect data on their presence and/or use in households to either rule out or flag such households in the analysis. Take-up of other demand-management programs can also bias results when it is not properly accounted for. Again, this needs to be handled by flagging (by date) or eliminating households that have been involved in other programs.

5.3 Data processing

Processing the data that is used to evaluate water savings can often constitute the bulk of the work. Primarily, this involves ensuring the reliability of the data, but it also often involves allocating CMDD into regular intervals ('binning') and linking data from different sources.

5.3.1 Segregating single and multiresidential dwellings

The primary step in any evaluation involving CMDD is to segregate single detached dwellings from multiresidential dwellings. There are two reasons for doing this. First, multiresidential properties are generally not individually metered, meaning that any reductions in water usage from a particular flat, unit or apartment will be diluted by other non-participating residences connected to the same meter. For this reason, evaluation studies tend to focus exclusively on individually metered single detached dwellings. Second, single dwellings usually have a significant outdoor component to their usage profile, whereas higher density dwellings have lower outdoor demand or none at all. Thus, comparing single and multiresidential households in a participant–control type method (see Section 5.4.2) to discern water savings from an indoor water-efficiency measure such as a showerhead replacement is likely to produce erroneous results. Differing occupancy ratios between dwelling types can also affect the way savings are extrapolated across residential sectors, as described in Box 5.1.

Box 5.1: Extrapolating savings from single detached dwellings to multiresidential dwellings

Where evaluations are performed on single detached dwellings only, it is often useful to extrapolate the results to multiresidential dwellings so as to calculate total savings from the program. In such instances, it must be recognised that the average occupancy ratio of single detached dwellings is typically higher than that of multiresidential properties. This has implications for extrapolating savings from single to multiresidential dwellings such that for most programs the savings will be slightly lower for multiresidential dwellings. Therefore, when evaluating the impact of a program as a whole, savings derived from an analysis of single dwellings that are to be extrapolated to the multiresidential sector should be adjusted according to local occupancy ratio figures.

5.3.2 Removing properties that have changed ownership or tenancy

Changes in property ownership or tenancy during the analysis period can potentially bias the outcomes of the analysis because the new household composition will inevitably cause a change in the water usage profile, rendering both before–after and participant–control comparisons untenable. This is particularly the case in evaluations that are performed on disaggregated (household) time series consumption data, such as matched pairs means comparison analyses and panel data regressions.

In panel data regression analyses informed by survey data, data on ownership/tenancy changes can be collected through the survey and incorporated directly into the analysis by limiting the data associated with each household to the period of continuous ownership/tenancy around the program intervention.

In matched pairs means comparison analyses of billing data, however, the effect of changing occupancy can be eliminated, or at least minimised, by removing from the analysis all households that undergo change of ownership during the analysis period and all rental properties (where this data is available). Where that is not possible, it simply must be assumed that the bias introduced by changing ownership/tenancy (inflating or deflating savings estimates) is self-cancelling, which is the unstated assumption of aggregate analyses anyway.

5.3.3 Cleaning

Data cleaning is an essential step to ensure a reliable, unbiased estimate of water savings. The data must be checked for anomalies such as negative, null or zero reads. Negative entries are often manual corrections to erroneous entries and unless the analyst is familiar with such data manipulation it is generally wise to remove records containing negative values. Null entries are mostly a problem when they create gaps in the record, while zeros may indicate inactive properties. When analysing data in time series, discontinuous records (that is, records with missing entries) might need to be removed to allow the data to be binned (see the following section). Tests for statistical outliers may also be applied to consumption data to reduce the bias associated with abnormally high (and potentially erroneous) records.

5.3.4 Binning

An important characteristic of CMDD is the meter read frequency, as it can influence the selection of the method used to evaluate water savings. The frequency with which meters are read (monthly, quarterly, biannually or annually) can vary between different water service providers and different customers. It may be useful to aggregate or disaggregate the period over which the data is analysed into daily, monthly, quarterly or annual water use. Each has advantages and disadvantages. An annual average may be simplest, but several years of data will be required to assess the impact of the program and detect whether the savings are significant.

Apportioning demand into uniform monthly timeslots can be particularly useful in revealing seasonal effects and savings that are obtained mainly in one season (such as savings from garden products or swimming pool covers). However, meter readings for residential customers are likely to be undertaken only quarterly (or less frequently). Furthermore, it is unlikely that all meters are read at the same point in time during a three-monthly interval because the walk route for all residential customers may take between one and three months to complete in any one billing cycle. This means that although all the CMDD for a given quarter was read within one billing cycle, say quarter 3 (January to March), the actual read dates could be, for example, anywhere from 31 January (recording the volume of water used from 1 November to 31 January) and 31 March (the volume of water used from 1 January to 31 March).

This misalignment of meter readings precludes grouping the data en bloc into distinct quarters or months. This can be overcome by 'binning' CMDD for each individual customer into synthetic monthly reads, which align water usage, as far as feasible, with the months in which the water is actually used. Monthly binning helps to add resolution to the seasonal profile of demand, but it also has a smoothing effect because consumption apportioned to each month is informed by the other months that sit within the associated meter read period. In the absence of more sophisticated water metering such as automatic meter reading (AMR), now commonly termed 'smart meters'), which can record consumption data at a much higher resolution (such as hourly or daily), binning is the best technique available to allow direct comparisons between individual CMDD records and aggregations of CMDD on a universal time step. Details on the technique of data binning are provided in Appendix 5A.

5.3.5 Linking datasets

In evaluations of residential efficiency programs, data on program take-up must be linked to consumption data. Where cross-sectional analysis is employed (see Section 5.4.3), the links need to be extended to data on household characteristics. This typically requires a unique property identifier such as the billing account number, although such codes are not always common to all datasets. In such cases the analyst must resort to other identifiers, such as block and section numbers or addresses, to link the data.

5.3.6 Separating different programs

Where the aim of the evaluation is to show the effect of a particular program intervention (say, Program 1) and a non-regression methodology is to be adopted for the analysis, participants in multiple programs (for example Programs 1, 2, and 3) must be excluded from the assessment of Program 1 and assessed separately as participants in all three programs. This is because synergistic effects can produce higher combined savings, while competition effects can make combined savings lower (Billings and Jones 1996). A synergistic effect would be, for example, a behaviour change program influencing various end uses across the home combined with a structural change program such as a showerhead swap. An example of competing programs would be a retrofit program that included a showerhead component being run at the same time as a showerhead program administered by a different agency. Thus, it is possible that the savings from the combination of Programs 1, 2 and 3 are not necessarily equivalent to the sum of savings from Program 1 alone, Program 2 alone and Program 3 alone. The combined effects of multiple programs can potentially be explored in a cross-sectional or panel data regression analysis using interaction terms (see Section 5.4.3).

Note that households that have participated in one program cannot be used as controls for the evaluation of another program under a participant–control method, including the matched pairs means comparison approach (see Section 5.4.2). The exception to this rule is if the first program is implemented outside the study period of the other program.

5.3.7 Segregating by demographics

Households from different age, socioeconomic, ethnic and other groups are likely to demonstrate differing water usage profiles. Where data is available at sufficient resolution (for example, collector district data from the Australian Bureau of Statistics) and participant sample sizes are large enough, the data may be segregated into demographic categories to provide specific information on the relative effectiveness of the program in particular groups. This step may be performed in either pre- or post-processing (that is, before or after the analysis of water savings).

A simple segregation that may generate useful information relating to program design and rollout is that between owner-occupied and tenanted properties data, which some utilities will already have at their disposal. Other forms of data segregation will generally require data from external sources or primary research.

5.4 Techniques for evaluating savings from demand-management programs

Techniques for estimating water savings from demand-management programs range from simple before–after comparisons of consumption figures to detailed regression modelling that attempts to explain household water demand using an array of time series and cross-sectional variables. The most basic techniques, such as the before–after test, may only be applied when all external factors, such as climate and water restrictions, remain constant over the period being analysed. In most situations, however, external factors are variable, and more complicated techniques, such as matched pair means comparison or regression models, are required to produce robust savings estimates.

As a first step in many water saving evaluations, aggregate CMDD can be plotted as a time series in order to help understand the influence of the initiative of interest, as well as the effects of various external factors (such as water restrictions). This can help the analyst understand the context and likely magnitude of the water savings and will aid in the selection of an appropriate technique to undertake a more thorough evaluation. It can also be helpful to employ simpler estimation techniques in a preliminary analysis to generate initial rough estimates of the expected savings. Those values may be used to validate the findings from the more complex techniques of the full analysis, helping to ensure that the techniques are applied correctly.

As mentioned above, data availability can be a critical constraint on the analysis approach adopted for an evaluation. For example, without household and/or demographic data, complicated cross-sectional or panel data regression (see Section 5.4.3) are simply not possible. Indeed, the matched pairs means comparison was specifically developed to provide a powerful evaluation method in the absence of such data. However, expertise and resources may also be a limiting factor (pair matching requires significant programming and database manipulation skills). Where such expertise is unavailable, resources may be better directed at collecting the demographic data for regression modelling if the analytical team is more familiar with that approach.

The following sections describe the principles behind the various techniques available to measure water savings from demand-management initiatives. The order in which the techniques are presented generally corresponds to the amount of data required to perform the analysis, beginning with the technique that requires the least data.

5.4.1 Basic before–after test

A simple test may be performed to evaluate water savings from a residential demand-management program using only water consumption data from participating households before and after the program's initiation. The difference between the participant's consumption before and after the program's initiation is used to approximate the water savings associated with the program. Water consumption may be compared at various time scales, including years, quarters and months. However, sub-annual before–after differences must be calculated from time intervals separated by 12 months (for example, 5 January to 6 January, or quarter 1 2005 to quarter 1 2006) to attempt to reduce the potential effect of seasonality.

The equation to determine water savings using the basic before–after test is:

$$\frac{\sum_{i=1}^{n}\left(P_{i,t,after} - P_{i,t,before}\right)}{n} \qquad 1$$

where

t = the time interval of interest

$P_{i,t,after}$ = the consumption of the i^{th} participant household at time t after the water efficiency program intervention

$P_{i,t,before}$ = the consumption of the i^{th} participant household at time t prior to the water efficiency program intervention

n = the total number of participant households.

The before period can be defined using just 12 months of data. When more than one year of post-intervention data is available, data from all years is compared to the same 12 months of pre-intervention consumption data.

The statistical significance of the average savings estimate can be tested using a repeated measures t-test. To perform this test, the data is typically entered into a statistics software package as the two original sets of consumption figures (aligned by household) rather than as the calculated differences. The test calculates the differences as part of the routine to then examine whether the average of the differences is significantly different from zero. Unlike raw consumption data, the before–after differences that represent savings are likely to be normally distributed, allowing the use of this parametric test. However, where the distribution of savings is significantly non-normal, the non-parametric equivalent of the repeated measures t-test, the *Wilcoxon signed-rank test*, can be used. Methods for assessing the normality of a sample distribution are described in Box 5.2.

Box 5.2: Assessing the distribution of evaluation data

Parametric means comparison methods such as t-tests and analysis of variance (ANOVA) work on the assumption that the data being tested is normally distributed. Such methods are accurate and powerful when the assumption of normality is satisfied, but can produce misleading results when it is not. The assumption is often violated when raw consumption figures are compared, as water-use distributions are typically positively skewed. Skewed distributions are less of a problem when analysing consumption differences, for example differences between before and after consumption or between matched participant–control pairs (see Section 5.4.2). Nevertheless, normality should be assessed prior to applying a parametric method to either form of data to ensure that the results from the analysis are reliable. Visual appraisal of a data distribution can be made using histogram, stem and leaf, and normal quantile plots. Numerical tests for normality include the Shapiro–Wilk test and the Kolmogorov–Smirnov test.

The test of significance used in the analysis chosen depends on the assertion to be made. Two-tailed tests are used to test whether average post-intervention consumption was either lower or higher than average pre-intervention consumption, whereas one-tailed tests are typically used to test only whether post-intervention consumption was lower (Dziegielewski et al. 1992). A one-tailed test is generally used (Dziegielewski et al. 1992) because it is more important to determine whether there were legitimate savings from the water efficiency program and little importance is placed on determining anti-savings (that is, when the water efficiency program caused consumption to increase). If the mean after consumption is found to be significantly lower, it is inferred that there were actual savings from the program.

While the simplicity of this technique may be appealing, it is subject to a number of major limitations. Foremost, it does not adequately account for external factors that could also cause household water usage to change over the intervening period and thereby bias the savings estimates, such as climatic variability or changes to water restrictions, price or regulations. To limit bias from such sources, comparisons should only be undertaken on time spans that do not encompass such factors, which may limit the analysis to a small segment of the sample or preclude it altogether. Alternatively, if the average effect on demand of the external factors is known, it can to some extent be factored into the savings calculation, although this is likely to be less reliable.

The effects of weather-induced variability can be overcome by comparing periods of very similar weather conditions, which is difficult to verify, or by applying some form of climate correction to the CMDD (see Fyfe et al. 2010, Chapter 3 in this document). However, since climate correction can itself be a complex analysis, it is preferable to undertake a more rigorous savings analysis if the data is available, rather than to attempt to apply a separate climate correction.

In situations in which only participant data is available, the basic before–after test is the only option available to estimate water savings. However, obtaining CMDD from non-participant households is generally encouraged so that participant–control methods (see below) may be employed to better account for external factors that may otherwise bias the results from the analysis.

5.4.2 Participant–control means comparison methods

Participant–control means comparison (PCMC) methods attempt to control for external factors by comparing changes in participant consumption over time with corresponding changes in consumption of a non-participant ‘comparison’ or ‘control’ group. Household savings are calculated at the aggregate level as the average of the differences between participant consumption before and after the intervention, minus the equivalent non-participant average. Statistical tests are used to determine the significance of any differences between the groups. The assumption is that both groups will be affected in a similar manner by any external factors (pricing changes, restrictions, climate etc.). In practice, that assumption is not entirely valid, as participants are typically self-selecting, which immediately sets them apart from the broader population of water users.

Ideally, participant and control households would be randomly selected before the program is initiated. This would constitute a statistically robust test of the program's effectiveness based on an experimental design that satisfies the assumption that all households in the analysis are randomly sampled from the same parent population. For water efficiency programs, however, such an approach is often not practical because the program is made available to all customers in the service area and participation is voluntary (thus self-selecting) and indeed is encouraged to maximise net water savings. Consequently, the identification of those who do not participate in the program as a basis for comparison occurs retrospectively. These non-participants are more accurately referred to as a 'comparison' group rather than as a 'control' group, but the term 'control' is often loosely applied (Dziegielewski et al. 1992).

Fundamentally, a self-selected participant group and a control group that is defined (by default) as those who do not voluntarily participate in the program in question do not represent samples from the same parent population. More specifically, self-selection can lead to a bias towards participants who are to some extent already attuned to water efficiency and likely to exhibit lower average water usage. However, if such a design is used with sufficiently large samples, the method can produce informative, if not reliable, results (Dziegielewski et al. 1992). Moreover, it is possible to assess the similarity of participant and control groups by looking at the distributions of their respective consumption data in the lead-up to program implementation (see Section 5.4.2).

The control group may comprise all non-participating households in the database, or a random sample of non-participating households. However, a sample of control households should be representative of the parent population that participants are drawn from. For example, if participants are known to be confined to a particular geographical area, the control group should be drawn from the same or an adjacent area. This assists in reducing the effects of geographically specific external factors, such as mains pressure and climate.

Cross-referencing against demographic and household data may also help ensure that participant and control households used in the comparison respond to external factors in a similar manner. However, where such data is available, more sophisticated analyses should be considered, since simple grouping by demographics and household characteristics cannot account for variability introduced by attitudinal and behavioural differences.

Alternatively, running a dedicated pilot evaluation as described in Box 5.3 would provide an opportunity to gauge the effectiveness of a program early on, with sufficient control to ensure the statistical robustness of savings estimates and eliminate complicating factors that could confound the analysis.

Box 5.3: Applying a statistically valid experimental design to evaluate water efficiency programs

A potential solution to the problem of sampling participants and controls from different populations is to set up a pilot study that randomly selects both participants and controls from a self-selected subpopulation. That subpopulation is first identified through a broad survey asking households to nominate themselves as candidates for taking part in the water efficiency program. A fraction of the self-nominated households is then asked to immediately participate in the program; the remainder are left to act as the control group (and to receive the program intervention after the study is completed). By drawing participants and controls from the same self-selected subpopulation, the first fundamental assumption of the comparison of means tests is theoretically satisfied. However, close consideration must be given to managing the pilot so as to minimise the potential for voluntary structural and behavioural changes among the control group.

To obtain significant results from such a study, a minimum sample size for the pilot should first be established using the following equation (Dziegielewski et al. 1992):

$$n=\frac{\left(s_p^2+s_c^2\right)\left(t^2\right)}{\left(\overline{C}_p-\overline{C}_c\right)^2} \qquad 1$$

where

n = the minimum number of participant (and control) households required to sample in order to obtain significant results, assuming that the sample sizes of the participant and control groups are identical

t = the t-statistic associated with a particular level of significance (e.g. p = 0.05)

s_p = the expected consumption standard deviation of the participant group

s_c = the expected consumption standard deviation of the control group

$\overline{C}_p$ = the expected average consumption of the participant group

$\overline{C}_c$ = the expected average consumption of the control group

The difference between the expected average of the control and participant groups may be approximated from previous studies or by using a fixed parameter or end-use approach. The expected standard deviations of the control and participant groups may be assumed to be both equal to the standard deviation of all consumption figures in the utility database. Alternatively, average consumption can be used, which effectively assumes that the coefficient of variation of the entire population is equal to 1 (Dziegielewski et al. 1992).

Comparing the participant and control sample distributions

The main concern associated with applying participant–control methods to groups that, because participant self-selection, are not drawn from the same population is that the groups may respond differently to external factors such as water restrictions, thereby biasing the savings estimates. While the integrity of the assumption of a common parent population cannot be assured when an evaluation is not based on a randomised experimental design (as per Box 5.3), a number of diagnostic analyses can be conducted to assess the validity of the assumption. Simple box plots of participant and control consumption over the same time interval can give an indication of the spread of the data, while histograms of the same information can be used to compare the shapes of the data distributions. Table 5.1 presents a number of non-parametric statistical tests that can be used to directly compare participant and control consumption distributions before the intervention. While a result that indicates that the null hypothesis is true does not guarantee that the samples are from the same parent population, it does suggest that the self-selection has not generated an overtly biased participant sample and that therefore the ‘default’ set of controls is a legitimate reference case.

Table 5.1: Non-parametric tests to compare the distributions of control and participant consumption before program commencement

Test	*Null hypothesis*
Independent samples Kolmogorov–Smirnov test[a]	The participant and control consumption samples have been drawn from the same population (or from populations with the same distributions).
Independent samples Mann–Whitney U test	The participant and control samples have been drawn from the same distribution (or from populations with the same distributions).
Independent samples median test	The medians of the populations from which the participant and control samples are drawn are the same.
Independent samples Moses test of extreme reaction	The range of consumption is the same across participant and control samples.

a This test can also be used to compare a distribution with a theoretical (e.g. normal) distribution.

Comparison of before–after differences between participants and controls

The logical extension of the basic before–after test on participants is to compare the average of the before–after consumption differences with the average of before–after differences for the same timespan in a control group. The average before–after difference in participant consumption calculated using equation 1 is compared to the corresponding control average:

$$\frac{\sum_{i=1}^{n}\left(C_{i,t,after} - C_{i,t,before}\right)}{n} \qquad 2$$

where

$C_{i,t,after}$ = the consumption of the i^{th} control household at time t after the demand-management program intervention

$C_{i,t,before}$ = the consumption of the i^{th} control household at time t prior to the demand-management program intervention

n = the total number of control households.

Net water savings are simply the difference between equations 1 and 2.

While the consumption data within the participant and control groups is aligned by household (generating the before–after differences), there is no alignment in the data between the two groups. Hence the comparison of the two groups is based on the *independent samples t-test* (one-tailed) or its non-parametric equivalent, the *Mann–Whitney U test*, and the test is performed on the two sets of differences, not the original consumption data. The non-parametric test is only required in cases where the before–after differences are not normally distributed.

Different forms of the independent samples t-test are applied, depending whether or not the before–after consumption differences are drawn from distributions of equal variances. *Levene's test* for equality of variances may be used to assist in deciding which form of t-test to use. This test is predicated on the assumption that the samples are independent, which in this case is satisfied, given that there is no relationship between the control and participant groups that could influence water usage or the change in water usage over time.

Two-way analysis of variance

An alternative statistical analysis of before–after participant–control data is two-way (factorial) analysis of variance. The analysis of participant and control groups described in the previous section effectively reduces four separate datasets to two by taking the before–after differences. In this way it can be considered to be a one-way analysis of variance (ANOVA) that looks at the effect of one *factor* (involvement in the program) on the before–after consumption differences. Two-way ANOVA can be used to perform the same comparison without having to calculate differences by considering the effect on water consumption of both the involvement and time *factors* (the main effects), the interaction between the two factors (interaction effect), and the variation *within* the treatment groups (the four combinations of the two factors) that constitute the error term. In this particular application of factorial ANOVA, the interaction effect is of most interest because it represents the change in water consumption relative to pre-intervention average consumption adjusted for control household demand. The analysis is set up as per Table 5.2, where μ is the mean water consumption from participant or control groups in a specific period before or after the program intervention and a time step of one month is assumed. The *levels* of the 'involvement' factor are 'participant' and 'control', while the levels for the 'time' factor are 'before (month *t*)' and 'after (month *t* + 12)'.

Table 5.2: Factorial ANOVA of water consumption data for savings evaluation

	Participant	Control
Before (month *t*)	$\mu_{Participant,Before}$	$\mu_{Control,Before}$
After (month *t* + 12)	$\mu_{Participant,After}$	$\mu_{Control,After}$

The two-way ANOVA model is:

$$x = \mu + \alpha_i + \beta_t + \gamma_{it} + e_{it} \qquad 3$$

where

x = values of water consumption

μ = the grand mean

α_i = involvement effects

β_t = time effects

γ_{it} = interaction effect

e_{it} = error term.

Factorial ANOVA is generally implemented through a general linear model (GLM) framework in standard statistical software packages such as SPSS or SAS. One advantage of ANOVA (when implemented through a GLM framework) over the t-test method is that it can accommodate an unbalanced design (that is, different sample sizes not only between groups but also across time). However, to ensure sampling integrity, a proportional design is recommended, in which the difference in the participant and control group sample sizes should be proportional between the participant and control groups. Another advantage of ANOVA is its ability to compare multiple programs (or subprograms) in the one analysis by assigning a level for each program of interest under the *involvement* factor.

Like t-tests, ANOVA assumes independent samples and normal distributions. It also makes the assumption of homogeneity of variances between samples (see 'Comparison of before–after differences between participants and controls'), which, along with the assumption of normality of distributions, will often not be satisfied when analysing water consumption data. Generally this is overcome by taking a logarithmic transform of the data prior to the analysis.

Close attention must be paid to the definition and coding of the reference case, as this influences the sign of the interaction effect and thus the expression of the result as a rise or reduction in consumption. Where data is log-transformed, the calculation of savings changes with different coding of the factors. Generally, the reference case should be defined as the treatment group in the period before the implementation of the water conservation program. When using raw consumption data, the water savings will be expressed directly by the 'interaction' term. If the value is positive, it will correspond to savings from the program, whereas if it is negative, savings were not achieved. When using logarithmically transformed data, the following equation can be used to calculate the percentage savings associated with the demand-management program:

$$S = 100 \times \left(1 - \frac{10^{\mu - \gamma_{it}}}{10^{\mu}} \right) \qquad 4$$

where

S = the percentage reduction in consumption related to the demand-management program

β_0 = the intercept

β_i = the coefficient associated with the interaction term (between group and time period).

Average savings can then be calculated as average participant 'before' period consumption multiplied by the percentage reduction. In order to calculate the confidence interval associated with the savings, the upper and lower 95% confidence interval values for the coefficient associated with the interaction term should be substituted into the above equation.

ANOVA relies on the assumption (discussed under 'Comparing the participant and control sample distributions') that participant and control households are taken from the same population. In situations where the means from the two groups in the before period are found to be significantly different, an alternative sampling or analysis approach such as the matched pairs means comparison technique (see below) should be considered.

Matched pairs means comparison approach

While the basic participant–control methodology can potentially be applied to a select random subset of the population to insure against distributional bias, that might not be cost-effective or even possible if the program has already been initiated. In that case, the most effective way of overcoming problems associated with assigning an appropriate control group to self-selecting participants in an ex-post evaluation is to individually match pairs of similar households according to their water usage profile. Randomised sampling is effectively replaced by a statistically driven process of carefully constructing a control group to ensure that the characteristics of participant and control groups are similar. This is the basis of the matched pairs means comparison (MPMC) approach, which is arguably the most powerful technique for evaluating savings from demand-management programs when only program take-up and water consumption data are available.

Residential water consumption is driven by factors external to the household (such as climate, weather and water restrictions) as well as internal factors (household occupancy, household type, installed appliances, behaviour etc.). Two similar households would theoretically be influenced in the same manner by all external factors. However, if an indoor structural change (such as the installation of a water-efficient showerhead) affects one household, that household will show a changed water consumption profile, reflecting the isolated impact of a single factor. Water savings can then be estimated from the observed difference between water-use patterns of households in a control group and patterns in a group of program participants.

Under the assumptions that short-term water use dynamics are relatively constant, and that participation in demand-management programs does not substantially change a household's other water-use habits, a control group can be established by identifying a matching non-participating household for each participating household. Matches between individual participant and non-participant households are identified primarily using a comparison of water consumption patterns prior to the participants' involvement in the program. Water consumption of the paired households can then be compared before and after the intervention (program implementation), with the divergence in consumption during the after-intervention period representing the water savings resulting from the program.

By identifying controls on a household-by-household basis, the process generates a control group of the same size as the participant group and allows savings to be calculated on an individual household level. This in turn reduces the test of statistical significance of savings to a simple repeated measures t-test. Moreover, the control group can be considered more reliable in controlling for the influence of external factors. Hence, under the assumption that the matched participants and controls respond equally to all factors influencing water consumption, the observed differences in water consumption between participant and control households following the initiation of the program are deemed to represent the isolated water savings associated with the program.

Matching by household demand can be performed on monthly binned CMDD using a least squares approach to comparing participant pre-intervention consumption with the corresponding consumption of all candidate controls (see Section 5.8.2 for a detailed example). Following the matching of participant–control pairs, the baseline for each pair is established by calculating the monthly differences in consumption before the program intervention. These baseline differences should be close to zero if participant–control pairs are well matched. The same differences are also calculated for each month after the intervention. Monthly water savings are calculated as the change in the difference between participant and control consumption over 12-month periods spanning the intervention, as per Table 5.3. The average savings for each month are then tested using a repeated t-test in a similar manner to the before–after test (Section 5.4.1).

Table 5.3: Calculation of net monthly average per-household savings using matched pairs

	Monthly consumption (L/hh/d)				*Monthly savings (L/hh/d)*	
	Before (baseline) period		After period			
Pair ID	Month j	Month j+1	Month j	Month j+1	Month j	Month j+1
1	$\Delta(P1,C1)_{before,j}$	$\Delta(P1,C1)_{before,j+1}$	$\Delta(P1,C1)_{after,j}$	$\Delta(P1,C1)_{after,j+1}$	$\Delta(P1,C1)_{before,j} - \Delta(P1,C1)_{after,j}$	$\Delta(P1,C1)_{before,j+1} - \Delta(P1,C1)_{after,j+1}$
2	$\Delta(P2,C2)_{before,j}$	$\Delta(P2,C2)_{before,j+1}$	$\Delta(P2,C2)_{after,j}$	$\Delta(P2,C2)_{after,j+1}$	$\Delta(P2,C2)_{before,j} - \Delta(P2,C2)_{after,j}$	$\Delta(P2,C2)_{before,j+1} - \Delta(P2,C2)_{after,j+1}$
…	…	…	…	…	…	…
n	$\Delta(Pn,Cn)_{before,j}$	$\Delta(Pn,Cn)_{before,j+1}$	$\Delta(Pn,Cn)_{after,j}$	$\Delta(Pn,Cn)_{after,j+1}$	$\Delta(Pn,Cn)_{before,j} - \Delta(Pn,Cn)_{after,j}$	$\Delta(Pn,Cn)_{before,j+1} - \Delta(Pn,Cn)_{after,j+1}$
					Average Net Saving	Average Net Saving

Pair-matching considerations

To incorporate seasonal variations in consumption, a minimum 12-month period prior to each individual household's intervention is required for the pair matching process. The period can be set to 24 months for better matching results. However, a longer baseline period demands greater computational effort for only a marginal increase in match quality. If the assumption holds that the control household will respond in the same manner to external influences, it can be assumed that a 12-month match in water-use behaviour will be sufficient. Matches should be as close to the intervention date as possible. Ideally, the matching window for each participant household is defined according to the household's specific intervention date (as opposed to single program commencement date).

Datasets are often too large to be readily handled in standard spreadsheet software, requiring the process for matching to be automated either in the database itself, or using a statistical software package or a programming language capable of handling large arrays of data.

Secondary matching criteria can sometimes be used to both reduce the computational load and improve the matching process. Matching participant–control pairs from pools defined by criteria such as postcode (or other geographical boundary), occupancy, lot size or socioeconomic level reduces the processing time by limiting the bounds of the search for matches and helps to ensure that matched households have similar characteristics and/or water-use traits. However, with each additional criterion, the size of the pool of households from which controls can be drawn is reduced, potentially offsetting any improvements in match quality and increased processing speed.

Therefore, the number of criteria and the closeness of match required should be tightened or relaxed according to the individual situation. For example, matching demands within a 15% tolerance could be tried initially. If this produces multiple matches per participant, additional matching criteria could be used or the tolerance criteria could be tightened to 5%. If it produces less than one match per participant, it could be relaxed to 25% or secondary criteria could be dropped. Generally, the larger the sample pool, the greater the scope for strict matching criteria. When the sample size is limited, fewer criteria and less stringent tolerance might be warranted to ensure that an adequate number of households are matched.

It is reasonable to assume that, as with responses to other external factors, responses to restrictions would be the same between paired households and therefore should not affect savings estimates. Alternatively, where there are differences, they should average out in the overall estimate of savings. However, it has been observed that participant households can show a stronger conservation imperative than the broader population in response to restrictions, causing a bias in savings estimates when restrictions come into force after the program begins (Fyfe et al. 2009b). This effect can be overcome by analysing only those participants whose intervention occurred less than 12 months before or after (new) restrictions were introduced.

5.4.3 Regression analysis

Estimates of the impact of demand-reduction measures can also be obtained using regression modelling. In a similar fashion to econometric determinations of the elasticity of price and other factors (see Fyfe et al. 2010, Chapter 3 in this document), an independent variable (or set of variables) can be specified in a regression model of historical demand to represent the impact of a water efficiency measure (or suite of measures) (Dziegielewski et al. 1992). The magnitude of the regression coefficient associated with the water efficiency take-up variable may then be used to quantify water savings associated with a particular water conservation program.

Most commercial statistical packages can be used to construct regression models. All that is typically required is data preprocessing, in which data is aligned by time and/or household. This may involve data binning, depending upon the desired temporal resolution of the data.

Time-series regression

Time-series regression models, otherwise known as longitudinal regression models, typically predict aggregated (average) household water demand over time using weather and/or temporal variables and one or more variables defining the implementation of one or more demand-management programs. In this conventional form of water demand model, the climatic and temporal variables are used to define the observed seasonality in water consumption, allowing the remaining variation in water consumption caused by the demand-management programs to be explained by their respective variables. Where water restrictions are in effect, the impact is typically represented using dummy variables, the magnitudes of which define the reduction in average water consumption caused by restrictions with respect to a base year not affected by water restrictions. Price effects may also need to be included in the model, although because the model considers aggregate demand, generally only the more dramatic (for example, structural) adjustments to price need be accommodated using simple dummy variables.

Demand-management programs implemented in all participating households at a single point in time may also be defined using a single dummy variable, as for water restrictions. However, when a program is implemented in different households at different times, the analysis becomes slightly more complicated. In that situation, the simplest approach is to remove a 'block-out' period in which the program is implemented (Dziegielewski et al. 1992). Then the regression model may be calibrated using only data outside that period. The major limitation with this approach is the removal of potentially valid data in the block-out period, particularly when post-implementation data is limited and/or savings estimates are required soon after program implementation. A more refined approach is to create a continuous variable defining the cumulative number of households participating in the demand-management program at sequential points in time. Average household water savings are obtained by multiplying the regression coefficient of the cumulative variable by the total number of participating households.

A generalised form of a time-series regression model may be written as:

$$y_t = \beta_0 + \sum_{k=1}^{K} \beta_{1,k} W_{k,t} + \sum_{l=1}^{L} \beta_{2,l} R_{l,t} + \sum_{m=1}^{M} \beta_{3,m} P_{m,t} + \sum_{n=1}^{N} \beta_{4,n} E_{n,t} + \varepsilon_t \qquad 5$$

where

y_t	=	average household demand at time *t*
$W_{k,t}$	=	a set of *K* weather and/or temporal variables that explain the effects of season and weather at time *t* (*k* = 1,2, … *K*)
$R_{l,t}$	=	a set of *L* variables that explain the water restrictions in force at time *t* (*l* = 1,2, … *L*)
$P_{m,t}$	=	a set of *M* variables that explain changes to the water price at time *t* (*m* = 1,2, … *M*)
$E_{n,t}$	=	the cumulative number of households participating in the n^{th} demand-management program at time *t* (*n* = 1,2, … *N*)
$\beta_{,0,1,\ldots,4}$	=	regression coefficients to be estimated
ε_t	=	the error term.

If program take-up variables ($E_{n,t}$) are closely correlated (primarily, that take-up starts around the same time), it is best to produce a separate model for each program to avoid the problem of the correlated variables interfering with one another in the regression (multicollinearity). Details on the specification of (time series) regression models of water demand, including adjusting for seasonality in time series models, are presented in *Complementary analytical techniques for urban water forecasting in IRP* (Fyfe et al. 2010, in this document).

This form of analysis is best applied to aggregated demand from participant households only, so that the effect of the program of interest is not drowned out by the broader population. Thus the model is a form of before–after analysis that incorporates the effects of external factors. Despite the common use of BWPD in other forms of time series regression models for other forecasting and analysis purposes (Fyfe et al. 2010), it is generally not advisable to use BWPD for the analysis, to avoid diluting the effect of the demand-management program being investigated. The rare exception would be when there are very few non-residential customers in the bulk meter service area and the program has been taken up by the majority of households.

Covariate regression

Covariate regression models are a variation upon conventional time-series regression models that make use of a control (non-participant) group to help explain normal variability in demand instead of weather and temporal variables. The premise for the approach has been adapted from catchment water quality modelling (see Bishop et al. 2005, USEPA 1993) and expands on the participant–control before–after principles of ANOVA described above by introducing a continuous time dimension. Thus, in covariate models, most of the variability in the aggregate participant water consumption is explained using a variable defined by corresponding aggregate non-participant water consumption. In this manner, virtually all external factors influencing participant consumption, aside from the water conservation measure of interest, are explained by the average water consumption of the non-participant group. Water savings associated with the demand-management program of interest are again determined from the regression coefficient derived for the variable reflecting the cumulative number of households participating in the program.

This method acknowledges that the participant and comparison groups might not be drawn from the same parent population and allows for other variables to be incorporated into the model to account for differing responses to external factors between the groups. Thus, variables (typically dummy variables) can be used to explain divergence from the typical relationship between average participant and non-participant demand caused by water restrictions and significant changes to the price tariff structure. It is important to recognise that the variables used to represent water restrictions and price changes in covariate models are fundamentally different from those used in conventional time series models. The regression coefficients generated in covariate models do not represent the absolute effect of those external factors, but rather the effect on participant demand *relative to* non-participant demand. Hence those variables cannot be used to quantify the net effect of external factors in a covariate model.

A generalised form of a covariate regression model may be written as:

$$P_t = \beta_0 + \beta_1 C_t + \sum_{l=1}^{L} \beta_{2,l} R_{l,t} + \sum_{m=1}^{M} \beta_{3,m} P_{m,t} + \sum_{n=1}^{N} \beta_{4,n} E_{n,t} + \varepsilon_t \qquad 6$$

where

P_t = average participant consumption at time t

C_t = average non-participant consumption at time t

β_1 = the coefficient associated with average non-participant consumption.

As in conventional time series models, collinear take-up variables should not be included in the same regression. However, the take-up variables used in the model determine the data used to generate the average participant consumption. Hence participant consumption data should be the average of the participants in only the programs being modelled. As for participant–control means comparison methods, average control data should not include consumption data from participants in any known demand-management programs.

It is important to note that this method has had limited application to real data or comparisons with other benchmark methods (Fyfe et al. 2009abc). The case study presented in Section 5.8 documents the application of covariate regression to estimate water savings from a retrofit and rebate program and compares the results with estimates from the MPMC method.

Cross-sectional regression

Cross-sectional regression models analyse demand over a particular period in time (a given month, quarter or year) across a sample of individual water users (households). Such models attempt to explain variability in demand as a (linear) function of involvement in the program and other defining characteristics that influence water use.

In the most basic form of a cross-sectional regression model, water consumption would be predicted using only a single dummy variable indicating whether or not the program had been implemented at a given household. This form of model is analogous to performing an independent t-test between participants and non-participants on post-implementation data, so it is prone to the bias introduced by self-selection described above, as well as interference from external factors.

More powerful cross-sectional models incorporate additional household explanatory variables in order to build demand profiles of individual households. The variables may represent characteristics such as:

- occupancy
- income
- plumbing fixtures and water-using appliances
  - ownership (number of toilets, showers, dishwasher, pool etc.)
  - type (dual- or single-flush toilet, front- or top-loading clothes washing machine etc.)
  - usage (length of showers, number of dishwasher loads etc.)
- prevalence of leaks
- lot size and garden watering habits
- property value
- age/condition of house.

A generalised form of a cross-sectional regression model is:

$$y_i = \beta_0 + \sum_{j=1}^{J} \beta_{1,j} H_{l,t} + \sum_{k=1}^{K} \beta_{2,k} E_{k,i} + \varepsilon_i \qquad 7$$

where

y_i	=	water consumption for the i^{th} household over a constant period
$H_{j,i}$	=	a set of J household and/or demographic variables for the i^{th} household (j = 1,2,…J)
E_n	=	a set of K demand-management program variables (n = 1,2,…N)
$\beta_{0,1,2}$	=	regression coefficients to be estimated
ε_i	=	the error term.

Household variables need not be exhaustive in developing a complete demand profile, since the aim of utilising them is more to distinguish between households and explain interhousehold demand variability. Thus, the ultimate model specification may only require a handful of statistically meaningful household variables. Moreover, some variables can be considered proxies for others and care must be exercised to avoid multicollinearity (Fyfe et al. 2010) where explanatory variables are potentially correlated. For example, lot size or appliance ownership could be reflective of income, and the use of both variables in a model could produce misleading results.

It is worth noting that, unless the study area extends beyond the service bounds of a single water authority, variables for factors that are external to the household such as price and water restrictions are not necessary. Such factors apply to all households equally, and because cross-sectional models do not consider change over time there would be no variability in the factors that could be correlated with variability in observed demand. The same applies to weather variables in analyses of climatically homogeneous areas. Where the geographical bounds of the analysis extend across climate zones (for example, greater Sydney or south-east Queensland), weather variables may be required to explain differing underlying demand between zones.

A key benefit of household-level cross-sectional modelling is the ability to explicitly accommodate known competing factors, such as other demand-management programs. Rather than having to exclude households involved in other programs, additional explanatory variables can be incorporated into the model to explain the effect of competing programs. Similarly, multiple programs can be evaluated in the one analysis by including an involvement dummy variable for each program of interest. The model could be further extended to explore the synergistic or competing effects between pairs of programs by including interaction terms in the model, although the analyst is advised to consult specialised texts on regression modelling for guidance on the specification and interpretation of interaction terms.

Cross-sectional models comprising household-level detail are more likely to detect and accurately estimate savings than simple participant–control methods, and provide an alternative to the computationally intensive MPMC approach. Surveying for data collection, however, tends to be time consuming and expensive—a consideration that is likely to affect the size of the sample to be analysed. Thus, the choice to adopt a cross-sectional regression approach may be informed by other factors, such as accessibility of CMDD (surveyed customers can be requested to grant permission to access their records at the time of the survey) or the presence of numerous competing programs/factors.

Panel data regression

Panel data regression models integrate cross-sectional and time series variables into a single model that predicts demand over time at a household (rather than aggregate) level. By encompassing both spatial and temporal dimensions, the number of observations and the potential degrees of freedom of the analysis are increased, allowing the construction of more complex models with numerous explanatory variables. Individual household consumption is typically predicted using a variety of climatic, demographic and household characteristic variables, along with variables indicating the participation in demand-management programs.

A generalised form of a pooled time-series regression model may be written as:

$$y_i = \beta_0 + \sum_{j=1}^{J} \beta_{1,j} H_{l,t} + \sum_{k=1}^{K} \beta_{2,k} W_{k,i} + \sum_{l=1}^{L} \beta_{3,l} R_{l,t} + \sum_{m=1}^{M} \beta_{4,m} P_{m,t} + \sum_{n=1}^{N} \beta_{5,n} E_{n,t} + \varepsilon_{i,t} \qquad 8$$

where variable definitions are as previously described and subscripts *i* and *t* represent the household and the point in time, respectively.

As with cross-sectional regression models, the collection of household and demographic data can be expensive and time consuming, potentially restricting the size of the sample of households and thereby limiting the degrees of freedom of the analysis. Therefore, model parsimony is encouraged so as to restrict the number of closely correlated variables entering the model and to avoid overspecification.

The complexity of panel data handling, model specification and model estimation requires the use of powerful statistical software packages such as SAS, STATA and LIMDEP. The use of such packages, as well as the modelling task itself, requires a high level of expertise, and inexperienced practitioners seeking to analyse panel data are advised to refer to specialised texts on the theory of panel data regression.

Panel data models may take a number of forms, each having fundamentally different specifications. An outline of the different forms of panel data models is given in this section.

Constant coefficients models

The constant coefficients model, sometimes referred to as the pooled regression model, is the most simple form of panel data regression in that it assumes no significant unexplained temporal or cross-sectional effects. The model maintains constant intercepts and slopes for all variables in an ordinary least squares regression model that is specified as per equation 8 above. Since it is generally hoped that the independent variables selected for the analysis are sufficient for explaining the majority of observed cross-sectional and temporal water demand variability, a constant coefficient model would the preferred starting point for a panel data analysis.

Fixed effects models

When there are known to be likely gaps in the model specification such that either cross-sectional or temporal variation is not adequately explained, a fixed effects model may be employed. Group fixed effects models control for unobserved variables that differ between cross-sectional groups (households) but are constant over time. They allow the change in independent variables over time to explain the variability in the dependent variable by introducing dummy variables that change the model intercept for each group:

$$y_i = \beta_0 + \sum_{j=1}^{J} \beta_{1,j} H_{j,i,t} + \sum_{k=1}^{K} \beta_{2,k} W_{k,t} + \sum_{l=1}^{L} \beta_{3,l} R_{l,t} + \sum_{m=1}^{M} \beta_{4,m} P_{m,t} + \sum_{n=1}^{N} \beta_{5,n} E_{n,t} + \sum_{i=1}^{I} \beta_{6,i} X_i + \varepsilon_{i,t} \qquad 9$$

where

X_i = dummy variable representing the i^{th} household

$\beta_{6,i}$ = regression coefficients to be estimated.

Conversely, time fixed effects models assume that unobserved variables differ over time but are constant across households, and introduce dummy variables to change the intercept for each discrete time period.

$$y_i = \beta_0 + \sum_{j=1}^{J} \beta_{1,j} H_{j,i,t} + \sum_{k=1}^{K} \beta_{2,k} W_{k,t} + \sum_{l=1}^{L} \beta_{3,l} R_{l,t} + \sum_{m=1}^{M} \beta_{4,m} P_{m,t} + \sum_{n=1}^{N} \beta_{5,n} E_{n,t} + \sum_{t=1}^{T} \beta_{6,t} U_t + \varepsilon_{i,t} \qquad 10$$

where

U_t = dummy variable representing the t^{th} time period

i_t = regression coefficients to be estimated.

It is also possible to control for both cross-sectional and temporal variability simultaneously, but the introduction of so many dummy variables starts to compromise the degrees of freedom of the analysis. Another form of fixed effects model varies the slopes of variables as well as the intercepts, although again this can have a negative impact on the degrees of freedom, particularly when applying this to both cross-sectional and temporal variables. The selection of the most appropriate fixed effects model is best informed by a hierarchical significance testing process, with the constant coefficients model as the baseline for comparison.

There are two key limitations associated with fixed effects models. The first is that any cross-sectional variables that do not vary over time (such as the number of toilets or showers) have to be excluded from a fixed group effects model because they will be perfectly collinear with the group dummy variables and thus inestimable. Likewise, time series variables that do not vary between households (such as weather variables) would have to be excluded from a fixed time effects model. Second, when there are a large number of cross-sectional variables compared to time series observations, or vice versa, fixed group and time effects models, respectively, start to suffer from compromised degrees of freedom as the number of dummy variables mounts. The first limitation is in many cases likely to apply to models of water demand, in which case a random effects model may be preferable.

Random effects models

Like fixed group effects models, one-way random effects models are used to accommodate unexplained cross-sectional variability. However, instead of ascribing an additional dummy for every household, household-specific intercept terms are modelled as a random deviation from a mean. This essentially adds a cross-sectional specific component to the error term:

$$\varepsilon_{i,t} = \alpha_i + u_{i,t} \qquad 11$$

The generalised model equation then becomes:

$$y_{i,t} = a + \sum_{j=1}^{J} b_j H_{j,i,t} + \sum_{k=1}^{K} c_k W_{k,t} + \sum_{l=1}^{L} d_l R_{l,t} + \sum_{m=1}^{M} e_m P_{m,t} + \sum_{n=1}^{N} f_n E_{n,t} + \alpha_i + u_{i,t} \qquad 12$$

Two-way random effects models divide the general error into cross-sectional specific, temporal, and individual error components such that:

$$\varepsilon_{i,t} = \alpha_i + \lambda_t + u_{i,t} \qquad 13$$

The critical criterion that must be satisfied to use random effects models is that there is no correlation between the unobserved household- or time-specific random effects and any of the regressors. This assumption of orthogonality may be tested using the Hausman specification test, which has a null hypothesis that no correlation exists (that is, that the individual effects are orthogonal to the independent variables). Where there is no correlation, a random effects model is preferred to a fixed effects model because it is more powerful and efficient. Where the model specification fails the test, a random effects model would be inconsistently estimated and a fixed effects model is more appropriate to the analysis.

5.4.4 Summary

All of the approaches discussed in this section rely on CMDD from participant households in order to quantify savings from demand-management programs. Additional data requirements associated with each of the discussed techniques are summarised in Table 5.4. ‘Primary’ data refers to the data that is essential to the analysis. ‘Secondary’ data is that which can be directly incorporated into the analysis to improve and refine the savings estimates. Note that results from any analysis should be interpreted with regard to available climate, water restrictions, price, demographic or household data. Means comparison analyses can also be refined by targeting specific geographical areas or demographic groups.

All approaches require data on other programs running concurrently with the program of interest, to either exclude those households that are involved in the other programs (participant–control methods) or to define additional variables in a regression model to account for the effect of those programs. Most evaluation studies of residential programs are best targeted at single dwellings, as measured savings are not prone to dilution from non-participating multiresidential properties that share a single meter. Due to the sheer size of CMDD sets, data processing prior to the calculation and testing of savings tends to be a significant component of the overall evaluation process.

Table 5.4: Data requirements associated with techniques quantifying savings from water efficiency programs

Method	*Primary data*[a]	*Secondary data*
Basic before–after test	Program intervention dates	–
Basic comparison of means	Non-participant water consumption[b], program intervention dates	–
Before–after comparison between participants and controls	Non-participant water consumption[b], program intervention dates	–
Matched pair means comparison	Non-participant water consumption[b], program intervention dates	–
Cross-sectional regression	Program intervention dates, demographic or household data[c], non-participant water consumption[d]	Climate data[e,f]
Time-series regression	Program intervention dates, climatic data[e], water restrictions and price data	Production data (instead of participant water consumption)
Covariate regression	Program intervention dates, non-participant consumption data[d]	Water restrictions and price data
Pooled time-series regression	Program intervention dates, climatic data[a], water restrictions and price data, demographic or household data[c]	Non-participant water consumption[d]

a To accompany participant consumption data.
b Used to define 'control' consumption.
c Such as household size, dwelling type, local government area.
d Used to establish the reference case for the demand management dummy variable.
e Such as temperature, rainfall, evaporation.
f Where modelling across different climatic zones.

The selection of the most appropriate technique for evaluating savings associated with demand-management programs depends on a number of considerations. The simplest techniques are the before–after tests and the participant–control means comparison (PCMC) methods, which require only consumption and participation data and basic statistical knowledge. However, despite their simplicity, the techniques are fraught with limitations. Foremost, they do not adequately account for external factors, which may alter the consumption behaviour of the control and participant households, making it difficult, if not impossible, to isolate savings associated with the program being investigated.

In the (common) absence of data on individual household characteristics, the MPMC technique is the most rigorous and powerful for quantifying savings from demand-management programs. However, the development of an algorithm to conduct the MPMC is time consuming and requires a high degree of technical skill in computer programming. However, once the algorithm has been developed the technique provides relatively quick estimates of water savings after data preprocessing.

Regression modelling typically requires a similar degree of data processing to the MPMC approach, and for cross-sectional and panel data requires information on individual household characteristics. Models based on time series data alone are the coarsest of the three forms of regression discussed and are the least likely to produce an accurate estimate of savings. Covariate regression is an alternative to conventional time series models based on weather variables that uses non-participant consumption as an explanatory variable to improve the accuracy of the time series approach without the need for household data. This form of model, however, has not been widely applied and remains a less proven methodology. Covariate regression can also be applied to matched pair data from MPMC analysis in order to determine whether the control and participant households are responding to price changes and water restrictions in a similar manner, thereby verifying the legitimacy of the pair-matching process.

Cross-sectional regression models are able to discern subtle differences in water consumption between separate households using household and demographic data, which helps to isolate the effects of demand-management programs. The main limitation with this type of model, however, is the inability to consider changes to savings over time or to account for seasonality in water savings. Panel data regression models overcome this limitation through integrating time series data with cross-sectional data at the household level. Panel data models, however, demand a high level of expertise in model specification. Furthermore, data manipulation and model estimation require experience in using more sophisticated statistical packages such as SAS, STATA, R (PLM package), LIMDEP and SPSS (Advanced Statistics Module).

5.5 Techniques used to evaluate water savings from restrictions

The approach most widely adopted for evaluating water restrictions is time series regression modelling based primarily on weather variables. In a manner similar to regression analysis of demand-management programs, demand reduction related to restrictions is determined through examining the residual variance after the influence of climate (and other relevant broadscale variables, such as price changes) has been factored out. Effectively, it is a form of climate correction analysis (see Fyfe et al. 2010) that examines the change in the demand regime caused by the introduction of or change in water restrictions. However, unlike in analyses of demand-management programs, the effect of water restrictions is generally not explicitly modelled using an explanatory variable. Instead, the effect of restrictions is interpreted as the portion of water demand not explained by a model calibrated to a pre-restriction period when it is applied to the restricted period. In other words, water savings are calculated as the difference between what demand would theoretically have been if restrictions were not enforced and the pre-restrictions demand regime had remained, and the actual demand observed under restrictions.

A typical regression model used for evaluating restrictions would take the general form:

$$y_t = \beta_0 + \sum_{k=1}^{K} \beta_{1,k} W_{k,t} + \varepsilon_t \qquad 14$$

where

y_t = average household demand at time t

$W_{k,t}$ = a set of K weather and/or temporal variables that explain the effects of season and weather at time t (k = 1,2, … K)

$\beta_{,0,1}$ = regression coefficients to be estimated

ε_t = the error term.

The model would be calibrated to an unrestricted period of at least one year to capture seasonal variability. When using a monthly time step, a longer calibration period is desirable to ensure a robust model. The model equation produced by this calibration is taken to be representative of an unrestricted demand regime. The impact of restrictions is then the difference between observed demand over the restricted period and the corresponding predicted demand for the period calculated using the equation derived from the model calibration. This analysis assumes that all the variability not explained by the model is caused by restrictions. That assumption will never hold true in absolute terms, but it is considered a reasonable approximation of reality when the model adequately explains the variability observed in the pre-restrictions calibration period.

Since water restrictions typically apply to the entire residential sector and some parts of the non-residential sector, BWPD can be used for the analysis. This facilitates modelling on time steps as small as a day and requires far less data handling and manipulation. On the other hand, this limits the analysis to quantifying the broad effect of restrictions, precluding analysis of the particular sectors subject to restrictions. However, if the analysis is conducted on a bulk water zone known to be predominantly residential, the findings can be interpreted to apply to that particular sector.

While interpreting the restrictions effect from residuals is straightforward, it does not provide a direct means of evaluating the statistical significance of the savings estimates. Various techniques have been employed to gauge the significance of departures from predicted demand, such as checking whether observed demand falls within the confidence intervals of the model predictions or applying a t-test to compare residuals from the calibration period and the restrictions period (see Section 5.7.2). Alternatively, savings from water restrictions can be quantified by including restrictions as an explanatory variable (or set of variables) in a regression model that is fitted to a period that includes both restricted and unrestricted demand. In such a model, if the restrictions variable is appropriately specified and found to be statistical significant, the associated regression coefficient represents the savings achieved.

The main problem with using an explanatory variable to gauge the effect of restrictions is that the result is heavily influenced by the way the variable or variables are specified. In most regression models of water demand, restrictions variables have been based on a simple binary specification whereby each stage of restrictions is represented by a separate dummy variable. However, that may not be adequate because savings arising from water restrictions will often exhibit seasonality, peaking in summer when restrictions have the greatest effect. Using a dummy variable specification effectively forces the effect of restrictions into a single constant value, which could produce an inaccurate savings estimate and even cause the variable to not be recognised as significant. To reflect seasonality in savings, water restrictions may instead be specified using separate dummy variables for each month or season, requiring up to three or 11 dummies for each stage of restrictions, respectively. However, the use of multiple dummy variables can reduce the degrees of freedom and power of the analysis where the number of demand observations is small. An alternative specification could be the use of single dummy variables for each stage, combined with interaction terms that combine the restrictions dummy variables with a variable that has a similar seasonal pattern, such as temperature or evaporation. The interaction terms change the slope of the model with the introduction of restrictions, thus allowing the effect of restrictions to be amplified as temperature or evaporation rises.

5.6 Analytical pitfalls, limitations and potential solutions

Determining water savings from demand-management initiatives, particularly water efficiency programs such as residential retrofits and showerhead swaps, generally requires analysis of CMDD. This means that some form of data binning technique has to be employed to accommodate the variable timing of meter reads. Data binning may also be required to more effectively account for seasonality when meters are read more infrequently. For example, Weber (1993) contends that monthly or bimonthly meter reads are essential to assessing demand-management programs using regression, to generate an accurate representation of seasonality. However, there are examples in which datasets with larger meter-read intervals are used. In these situations, a binning technique needs to be employed to apportion reads into smaller time steps (monthly for quarterly read data, quarterly for biannual data).

One of the major limitations associated with the binning of long meter-read intervals into smaller consumption time steps is linked to the effect of ‘smearing’. In this situation, seasonal peaks and troughs might not be adequately defined in the data. As a result, it may be more difficult to match pairs and to specify representative climatic variables. Another major limitation associated with infrequent billing is that demand-management programs are often implemented between successive meter reads. This makes it difficult, if not impossible, to quantify the water consumption prior to and after the implementation of the program during the time interval. To overcome limitations associated with infrequent billing periods, during planning of evaluations, water service providers should either undertake special reads for participants or (preferably) undertake increased meter reads across the board. Alternatively, this period should be avoided in the analysis.

Past examples using regression models to determine the effect of water restrictions have tended to specify the restrictions variable as a simple dummy variable, without considering the potential seasonal variation in the demand response to restrictions. Given that most restrictions regimes are designed to limit outdoor water use, it is reasonable to assume that restrictions will reduce demand more in summer irrigation months than in winter. Kidson et al. (2006) and Spaninks (2010) accommodated seasonality in savings by analysing the difference between observed and predicted demand in the post-restrictions period rather than using a single dummy variable in the model itself. This approach, however, assumes that the regression model successfully explains all the non-restrictions related variance and that the entire portion of the post-restrictions error terms is the effect of restrictions—a necessary but coarse assumption that generates reasonable estimates of savings but perhaps requires further substantiation. In adopting this approach, it may be possible to explain more of the non-restrictions related variability in demand, such as that caused by gradual efficiency gains, by modelling seasonal demand and base demand separately (see, for example, Zhou et al. 2000). Alternatively, when specifying restrictions variables, consideration could be given to breaking up the effect into seasons (by using summer, spring, autumn and/or winter dummy variables) or interacting the restrictions variable with variables that are positively correlated to outdoor water use (primarily temperature and evaporation).

When using the results of savings analysis, care needs to be taken when incorporating the savings identified into the options component of the end-use based model. Projected savings of options need to take into consideration 'free riders' (the proportion of stock that would change over to more efficient stock through natural attrition anyway—especially in the case of rapidly changing technology such as washing machines). Hence, the interconnection of the end-use stock models with the savings models needs to be considered.

Table 5.5 describes additional pitfalls and limitations, along with potential solutions.

Table 5.5: Pitfalls, limitations and potential solutions associated with measuring the impacts of demand-management programs and water restrictions

Pitfalls and/or limitations	*Potential solutions*
Analysis limited to participants who may represent very specific groups	Actively select households participating in demand-management program.
Analysis limited to single dwellings	Submetering of multiresidential blocks. Weight the analysis by household size (occupancy).
Analyses of indoor programs need to control for outdoor use and rainwater tanks	Use strict matched pair validation criteria. Specify rainwater tanks and weather variables in a regression model.
Interaction of programs targeting the same end-use	Remove households participating in two programs associated with the same end-use.
Short pre- and post-intervention periods may not reflect the true success of the demand-management program	Use a minimum of 12 months for the pre-intervention period. Undertake evaluations later than two years following intervention to assess the longevity of the savings.
Analysis needs to take account of whether the fixture is a primary fixture (e.g. main or ensuite toilet)	Careful collation of such data at the time of supplying/rebating the fixture .
Results may be difficult to evaluate due to large variance in the signal	Use the largest possible dataset.
Difficulty separating the effect of water restrictions from demand-management programs if both are implemented at the same time	For regression modelling, collect additional data from when similar water restrictions were in place in the past. Use a pair-matching exercise to factor out the effect of the water restrictions.

5.7 Examples

This section summarises published examples of the application of some of the demand-management program and water restrictions evaluation methods described in sections 5.4 and 5.5. It provides an indication of the variety and complexity of numerical evaluation tasks and shows how the various techniques can be adopted and tailored for specific applications.

5.7.1 Demand-management programs

Matched pairs means comparison studies

A number of recent evaluations in Australia have adopted the MPMC approach to quantify water savings associated with a range of demand-management programs. Turner et al. (2005) successfully used the MPMC approach to evaluate water savings from households participating in the Sydney Water Corporation’s Every Drop Counts Residential Retrofit Program (now called ‘WaterFix’), which over the past 10 years has been implemented in more than 500 000 households in the Sydney region. At the time of program evaluation, approximately 200 000 households had taken part. The program involved a qualified plumber visiting the home to install tap flow regulators on kitchen and bathroom sinks, install toilet cistern flush arrestors, replace inefficient showerheads, locate and repair leaks, and provide general water-saving advice. An overall reduction in water usage associated with the program was first determined using the MPMC approach on 17 000 participating households, producing a savings figure of 20.9 ± 2.5 kL/household per year. The participant group was then broken down into subgroups according to which specific program components they received to analyse the potential synergistic and competitive effects on water savings. As a final part of the study, an analysis was undertaken to examine potential relationships between the estimated water savings and various geographical groupings, socioeconomic categories, income categories and occupancy ratios.

Kidson et al. (2006) used the MPMC approach to evaluate water savings associated with Sydney Water’s 2003 washing machine rebate program, which later informed a revised program in 2006. Household water consumption records were first put through data processing to remove multiresidential households, households experiencing a change in occupancy and unoccupied households. Participant households were then matched to other households in the same suburb, thereby accounting for the widely varying weather conditions occurring over the greater Sydney metropolitan area. Out of a possible 6545 households participating in the program, 1365 were successfully matched. The results showed that the savings were related to the type of washing machine owned prior to participation in the program: larger savings were observed in households previously owning a top-loader rather than a front-loader. The effect of outliers was also analysed, and results appeared more robust in terms of confidence interval widths after outliers were removed. Taking outliers into consideration, the overall program achieved a saving of 23.2 ± 5.1 kL/household per year for households taking up the 4A washing machine rebate. However, those that already had a front-loading machine only saved 16.9 ± 9.3 kL/household per year, compared to 29.8 ± 6.8 kL/household per year for those that originally had a top-loading machine.

The MPMC approach was also used to estimate water savings from the Home WaterSaver Rebate Scheme run by Gold Coast Water (Snelling et al. 2006, Turner et al. 2007). Water savings estimates were obtained for a number of water-efficient products, such as rainwater tanks, washing machines, shower roses and/or water flow regulators, spa covers, dual-flush toilets, garden products and pool covers. It was found that actual savings from rainwater tanks and washing machine rebates were lower than theoretical estimates. It was also found that water savings were likely to be lower if rainwater tanks were not connected to indoor end-uses, which help to optimise the potential savings of tanks, or if rebates were not restricted to well-designed water-efficient front-loading washing machines.

In an interesting extension of the MPMC approach, a mains supply pressure reduction program, also run by Gold Coast Water and designed primarily to reduce leakage and the impact of mains bursts, was evaluated in a separate study (Simard and White 2007) to determine the associated reduction in residential demand (that is, the effects of pressure reduction on the customer side of the meter). Individual households within the service areas affected by the program were matched to households outside the affected areas to provide the comparison group. The average saving across 14 000 households was found to be 16 kL/household per year. That figure was thought to be an underestimate of true savings because water restrictions and the Home Water Saver Rebate Scheme were in effect at the same time. Restrictions, in particular, are likely to deflate the savings observed because pressure reduction in a household is likely to achieve greater savings in large outdoor end-uses associated with flow rates (such as garden watering). With restrictions in place, less garden watering would be permitted and thus fewer savings would be achieved from a pressure reduction program. This demonstrates the complexity of evaluation studies and the need to always be mindful of other factors that may interfere with the analysis.

Regression studies

International papers published on evaluations of demand-management programs mostly describe regression methods. Morgan (1982) undertook a study to quantify water savings associated with the implementation of water conservation kits in Oxnard, California, using a pooled time series and cross-section regression analysis. Bimonthly water usage at individual residences was predicted using a combination of explanatory variables, including:

- property value
- number of years of residence
- occupancy
- house age and condition
- age of the head of the household
- the number of water-using appliances.

Dummy variables representing each billing period were used to explain seasonal and weather-induced variation, and to quantify longer term, temporal trends associated with water conservation publicity and associated demand reductions, and/or a declining real price of water. Participation in the conservation program through retrofitting a toilet flush reducer and a showerhead flow restrictor, and detecting leaks in toilets, was indicated by another dummy variable. Once the regression model was calibrated, the coefficient associated with the water conservation kit variable was used to estimate savings in water usage. The study estimated an average saving of 22.1 kL/household per year, or an approximately 4.2% reduction in consumption.

Morgan and Pelosi (1980) carried out another regression analysis on the dataset referred to above to account for the fact that participants tended to have higher average consumption prior to the program's inception. The difference in average (aggregate) bimonthly water usage between households that installed the kits and those that did not was predicted using a simple linear regression model incorporating a single dummy variable to indicate the period before and after the distribution of the kits. The coefficient associated with the kit installation variable was again used to determine the reduction in water usage. The 3.2% reduction in average bimonthly water usage was comparable to the 4.2% reduction obtained via the pooled time series and cross-section regression analysis described above.

Renwick and Archibald (1998) undertook a regression analysis on data from two Californian communities to determine the effectiveness of technological change, non-price policy and price policy in reducing water demand. A total of five separate equations were developed. Technological change was specified through the use of four separate equations, capturing the adoption of different indoor and outdoor water-efficient technologies. Water demand was then linearly regressed against the outputs from the four previously specified equations modelling technological change and a variety of other variables, which quantified socioeconomic factors and climatic influences as well as the implementation of price policy and non-price policy (such as water restrictions). Due to the simultaneity inherent within the model, a two-stage least squares estimation procedure was used to calibrate the model. After calibration, the regression coefficients were used to calculate elasticities associated with the various demand-management variables to infer their relative effectiveness.

Kenney et al. (2008) carried out a regression analysis on data from Aurora, Colorado, to measure water savings from indoor and outdoor water conservation measures, water restrictions and price policy. The natural log of household demand was regressed against a variety of seasonal/weather-related variables, economic/demographic-related variables and variables indicating the implementation of demand-management techniques (that is, price policy, water restrictions and water conservation measures). Most explanatory variables were not transformed, aside from median household income and the CPI-adjusted average price of water, which were both logarithmically transformed. The logarithmically transformed average price of water was also multiplied by a dummy variable indicating whether water restrictions were in place, to account for the fact that households constrained by restrictions are less responsive to price changes. As a result, the final regression model effectively incorporated the interaction between water restrictions and price policies.

5.7.2 Water restrictions

To gauge resident response to water restrictions in the Rouse Hill development in north-western Sydney, Kidson et al. (2006) fitted a regression model with average maximum daily temperature and rainfall as independent variables to binned and seasonally decomposed CMDD in the period leading up to the introduction of restrictions. The percentage reduction in demand associated with restrictions was then calculated as the difference between the total predicted demand using the regression model (that is, demand expected without restrictions) and observed demand over the subsequent restrictions period. The same analysis was also performed for a control group outside the development to compare responses between residents with a third pipe water supply (Rouse Hill) and those with conventional reticulation.

In a similar analysis of the impact of water restrictions on demand in greater metropolitan Sydney, Spaninks (2010) regressed temperature, rainfall and evaporation variables against monthly per capita demand derived from reservoir corrected BWPD and estimated population served. Demand was again adjusted for seasonality using seasonal decomposition, and the weather variables were normalised to the average for the period of analysis to represent deviations from average. The stepwise regression also included lagged weather variables, and generated a final model that used temperature, evaporation and previous day's rainfall as explanatory variables. As in the previous study, the water savings from restrictions were interpreted as the difference between observed and predicted demand during restrictions. The effect of concurrent demand-management programs on the results was explored but not explicitly quantified.

Neal et al. (2010) performed a very similar analysis to gauge the effect of water restrictions on three towns in north-east Victoria. Raw monthly demand (not adjusted for season or population) from BWPD records was modelled using evaporation and rainfall as explanatory variables. Again, percentage reductions in demand caused by restrictions were calculated from the residuals when the model, calibrated to a pre-restrictions period, was used to predict demand under restrictions. The analysis took an additional step to verify the statistical significance of the observed reductions by comparing the pre- and post-restrictions residuals using an independent t-test. For one of the three towns considered in the analysis, the model was a relatively poor fit and there was no significant reduction in demand related to restrictions. This was thought to be an artefact of the demand profile of a small town, which may be prone to variability caused by factors not included in the model, including tourist numbers (particularly in winter).

Morden et al. (2007) combined regression analysis with frequency analysis to reveal the changes in peak hourly demand associated with reductions in demand stemming from demand-management programs and restrictions in Melbourne. Regression analysis was used to describe the relationship between peak hourly demand and selected weather, water restrictions and trend variables. From this, two models for normalised peak hourly demand were developed: one based on current demand and a second calibrated to demand five years earlier. Frequency analysis was then used to generate 1 in 20 annual exceedance probability peak hourly demands from a time series of demand generated using historical weather data as inputs to the two models. The effect of water restrictions, expressed in terms of the percentage reduction in the 1 in 20 year peaks, was held to provide potential cost savings through the delay and reduction of system augmentations and reduced infrastructure replacement.

Beatty et al. (2008) applied climate correction to BWPD from Yarra Valley Water in Melbourne to reveal noticeable downward trends in production associated first with water pricing reforms and then with the introduction of water restrictions. Climate correction was also applied to CMDD from detached dwellings in Yarra Valley. A downturn in consumption following the introduction of restrictions was verified by demonstrating that the upper 95% confidence interval of the climate correction for the restrictions period fell below the lower confidence interval for the period leading up to restrictions. This approach was similar to that taken by Hansen and Narayanan (1981), who compared the observed demand with the predicted demand over a three-year period that included one restricted year. In this case, observed demand fell below the confidence interval of the predicted demand in the year of restrictions.[1]

Roberts (2008) used aggregate weekly sewer flows from Yarra Valley Water to determine the impact of water restrictions on indoor water use. Dummy variables were used to represent the effect of two water restriction stages on sewer flows in a simple linear regression model also incorporating rainfall and a trend variable (representing the effect of other demand-management measures) as independent variables. Savings associated with the restriction stages were gauged by the model coefficients associated with their respective dummy variables.

Chapman, in White et al. (2000), took the climate correction and trend tracking approach described in DEUS (2002). First, predicted demand from a climate correction model was plotted against observed demand for both the period immediately prior to restrictions and the restrictions period. Polynomial curves were fitted to the plots to generate expressions for predicted demand in terms of observed demand. Savings were then calculated for in-house (weather-independent) and ex-house (weather-dependent) demand by inputting observed values for each month into the two polynomial functions and comparing the outputs.

In a study conducted by Anderson et al. (1980), the effect of water restrictions on daily municipal water use in the city of Fort Collins, Colorado, was evaluated using multiple linear regression models. Various climatic variables, such as temperature, precipitation, solar radiation and evapotranspiration, were incorporated into the models, along with a maximum of three water restriction dummy variables. Two of the models only used one water restriction variable, which specified whether or not water restrictions were in place, whereas the third used an additional two dummy variables that reflected the proportion of the population affected by lawn watering restrictions on a given day. These additional water restriction variables led to more accurate predictions of daily water use by the third model.

5.8 Case study

This section documents the application of the matched pairs means comparison (MPMC) and covariate regression estimation techniques described above to evaluate water savings from two residential demand management programs:

- household retrofits of water-efficient taps and showers, leak repairs and water-saving advice (home water retrofit, HWR)
- rebates on the installation of a water-efficient Water Efficiency Labelling and Standards (WELS) scheme rated dual-flush toilets (DFTs).

The case study first details the processing involved in preparing the data for the analyses, including the criteria and rationale behind quality screening. The principles underpinning the implementation of the two analytical techniques are then described, followed by a comparison of the water savings estimates from the two techniques.

[1] Prediction intervals would be more appropriate for these analyses; see Fyfe et al. (2010).

5.8.1 Data processing

Intervention dates for each of the programs were first extracted from the program records. The toilet subprogram required that rebate applications could only be filed after the purchase, so the application date was used to indicate the intervention.

The program participation data then had to be linked to CMDD supplied by the water utility. Most subprogram records included a billing account number. Where a billing number had not been recorded, block and section numbers were used to identify the participant household's consumption record. All remaining non-participant household consumption records in the utility database were ascribed to the pool of potential 'control' households.

While the program was available to the entire residential sector, only single detached dwellings could be used in the analysis. Multi-residential properties are generally not individually metered, meaning that savings estimates generated from multi-residential data would be diluted by other non-participant properties. It was also important to ensure that there was no misattribution of water savings between programs. Therefore, households participating in other known demand management programs were removed from the participant subsets. Note, however, that only participants in the HWR retrofit were eligible to be recipients of the DFT rebate. Hence the effects of the two programs were effectively lumped in the analysis of the DFT rebate.

The participant and control datasets were then subjected to quality screening to remove households whose consumption records contained the following anomalous data:

- null (empty) consumption readings
- negative consumption readings
- zero consumption readings
- duplicate readings
- misaligned meter-read dates or missing readings (discontinuous records)
- statistical outliers
- intervention dates well outside the bounds of the program
- meter reads that occurred well outside the bounds of the analysis period.

The removal of households with one or more zero consumption readings ensured that households that were vacant or inactive or that underwent a change in occupancy were removed from the dataset. Households with duplicate and misaligned reads were removed to allow the binning algorithm, which relies on continuous consumption records, to standardise the data to a monthly time step. Unusually high levels of consumption were deemed likely to bias savings estimates. Hence, statistical outliers were defined as readings that exceeded the threshold:

$$10^{\mu \pm 2.5\sigma} \qquad 15$$

where:

μ = the mean of the logarithmically transformed data

σ = the standard deviation of the logarithmically transformed data.

This threshold is based on the understanding that in a lognormal distribution (which is typical of water consumption data) 99% of the data should be below this figure.

After the elimination of problematic data, the quarterly consumption data was binned into monthly consumption figures using the method outlined in Appendix 5A. This aligns household records to a universal time step, which enables the use of common reference points in time and facilitates direct comparisons between households. The monthly demand figures were divided by the number of days in the month and converted to units of litres/household/day (L/hh/d) so as to allow direct comparison between months.

5.8.2 Matched pairs means comparison analysis

The primary method used to estimate water savings from the programs was the MPMC technique described in Section 5.4.2. That method was considered to be the benchmark standard of the two methods used in this case study, as it had been developed, tested and refined through the course of a number of other evaluations, including Fyfe et al. (2009abc), Lee et al. (2007, 2008), Simard and White (2007), Snelling et al. (2006) and Turner et al. (2005). It can also be considered to be the more powerful of the two methods, primarily because it calculates savings at an individual household level to generate a cross-sectional average at each time step. The method consists of four steps:

- pair-matching
- quality testing of pair matches
- savings calculation
- null hypothesis testing.

Pair-matching

The core of the methodology consists of matching each single detached household that participates in a program ('participant') with a non-participating single detached household ('control'). This theoretically ensures that control and participant households are drawn from the same population, thereby avoiding the distributional bias discussed in Section 5.4.2.

Using a linear search algorithm, matching can be performed on an exhaustive comparison between each participant and all controls (that is, no sampling is used). A control household is identified by the least squares differences between monthly water consumption levels over the pre-intervention matching period. Matched controls are removed from the database to ensure that a unique control is identified for each participant, preserving the independence of each matched pair for later statistical analysis. Participants are not necessarily matched with the 'best possible' control but rather with the 'best possible control still available'.

The pair-matching algorithm calculates a match value for each participant and potential control. That value is the squared sum of differences between water consumption in each month for the participant and control, and reflects the quality of the match. The matching is done by means of least squares analysis, using the square-root difference between monthly consumption between the control and participant (also known as the Euclidean distance):

$$\sqrt{(C_{I-14} - P_{I-14})^2 + (C_{I-13} - P_{I-13})^2 + \ldots + (C_{I-3} - P_{I-3})^2} \qquad 16$$

where

P = monthly demand of participant

C = monthly demand of associated control

I = the month of the intervention.

To minimise the risk of other factors influencing water savings estimates, each participant was matched over the time period immediately prior to their participation in the program. Since water meters were read on a quarterly basis, the consumption values up to three months immediately before the intervention were in part influenced by the demand-management measure. For this reason, a period of between 14 and 2 months prior to the month of the intervention was used for matching. It should also be noted that the order of the participants in the database was randomised before matching to minimise any bias that may result from an ordered list of participants.

Any participant household that did not have adequate pre-intervention data to allow matching was eliminated. Then participants that did not have adequate post-intervention data were dropped from the routine. The savings calculation described below was applied to data from the third month after the intervention date onwards (because of the effect of binning quarterly data mentioned above). Therefore, only participants with at least three months of post-intervention data were retained.

Within the matching routine, a number of criteria were applied to the control households. Before a least squares calculation was performed, each control was tested to ensure that it had sufficient data that corresponded to the pre-intervention data of the participant being matched (that is, 14 months of data prior to the participant intervention date). A pair of secondary criteria was then used to identify optimum matches following the least squares calculation. Where a participant household had more than 12 months of analysable post-intervention data, a control match identified by the least squares calculation must have had 12 months of corresponding data to analyse. Where a participant had less than 12 months of data, the matched control must have had at least the same number of corresponding data points.

Applying the above criteria to the control group effectively resulted in a trade-off on the quality of matches (a slight reduction), in that a sub-optimum match could be selected in favour of the strongest least squares match on the basis of making use of available participant consumption data. Therefore, it was possible that no match could be found for a participant because there was no control remaining (given the stepwise nature of the matching) that had sufficient pre- and post-intervention data.

Quality testing of matched pairs

A good match indicated that the households had similar water consumption characteristics. Once the match value was obtained, there needed to be a process to determine whether the match was at a level appropriate for the analysis. Assuming the match criteria was appropriate for the majority of matched households, only those pairs of properties for which the match was not as good were further investigated. For example, the match value for high water users was likely to be higher—which implied a poor match, but in fact the value was higher only because consumption was of a higher value. Because high water users are part of any population, a filtering process that treats all customers equally was used to ensure that high water users were not discriminated against in the sample.

To ensure the statistical integrity of the matched pairs previously identified, they were validated using four tests:

- spur test
- mirror test
- correlation test
- variance ratio test.

The spur test was used first, to eliminate pairs that were not sufficiently robust to withstand finer grained validation techniques. Pairs that passed the spur test were subjected to the three other tests, while those that failed the spur test were discarded. Pairs that failed all three of the subsequent tests were also discarded. Thus, pairs that were retained for the means comparison analysis were those that passed the spur test and one or more of the mirror, correlation and variance ratio tests. The rationale behind each test is described below.

The spur test detected spurious consumption data points, which were defined as monthly consumption figures that were 12 times greater than a given participant household's long-term mean consumption. Thus, if a household used more water than its average annual consumption in a single month, that was considered to indicate a problem such as a meter-read error or a significant leak that would bias the water saving calculations. It is possible to use other multiples of monthly demand to identify anomalies; however, care must be taken to ensure that a lower threshold does not cause the remaining sample size to become too small to allow statistical inferences to be drawn from the analysis.

The mirror test was used to gauge the strength of the matches between participants and controls, placing a limit on the size of the match value of matched pairs. Since there is no absolute measure of the strength of a least squares result, the mirror test superimposes a normal distribution onto the histogram of match values from all the matched pairs. This defines a relative measure derived from the sample itself, against which to identify lower-quality matches. The match value calculation generates a skewed (log-normal) distribution of results with a lower bound of zero and a large tail to the right. The side of the distribution not skewed is mirrored at the geometric mean (GM) to define an acceptable upper limit. Thus, poor matches were defined as those least squares results that sit outside the range:

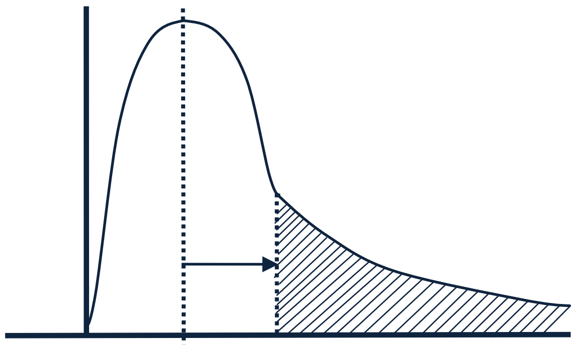
$$\begin{aligned}(Match\,value)_{MIN} &\leq (Match\,value)_i \\ &\leq (Match\,value)_{GM} + \left[(Match\,value)_{GM} - (Match\,value)_{MIN}\right]\end{aligned} \tag{17}$$

where

(Match value)$_{MIN}$	= minimum match value
(Match value)$_i$	= match value of the *i*th pair
(Match value)$_{GM}$	= geometric mean of match values.

When the minimum match value is zero, the upper bound becomes two times the geometric mean of all match values. To capture those matches where the match value is high *relative to* the consumption figures that it is calculated from, the quadrant test is also applied to the normalised match value results (that is, match value divided by the mean consumption of the matched pair control). The shaded section of Figure 5.1 represents the households that were next subjected to the correlation test.

Figure 5.1: Geometric mean of a skewed probability distribution



The correlation test uses Pearson’s correlation coefficient as an indicator of the closeness of the match between the participant and control profile. The coefficient is a figure between –1 and +1, with +1 signifying a perfect correlation. A negative value indicates negative correlation (that is, participant consumption goes up in months when control consumption goes down, or vice versa). Thus a higher positive correlation indicates greater confidence in the match. The correlation test adopted a threshold value of 0.96; pairs that had a correlation of less than 0.96 underwent further testing.

The final test applied was the variance ratio test, which was used to account for the possibility that both the participant and the control had near-constant consumption over the matching period (that is, low variance), which would give a low positive correlation even though the match was of an acceptable quality. A high variance ratio can also indicate a poor match, particularly when combined with low correlation. If the variance of the participant’s consumption was much larger than the variance of the control’s consumption, or vice versa, then the consumption ranges would be different and the match may be unacceptable. Thus the variance ratio was set between 0.5 and 2 for cases where the correlation was smaller than 0.96.

Savings calculations and paired t-test

Average monthly net savings were calculated using all active participants in each month. As per Table 5.3, the difference between the consumption of each participant and its corresponding control in the 'before' period (which corresponds to the matching period) was taken as the baseline against which to compare the difference between participant and control consumption after the intervention. Again, the effect of quarterly meter reads had to be taken into account: consumption values up to two months prior to or following the month of the intervention were regarded as being (potentially) biased by pre- or post-intervention use, respectively. Therefore, the first two months immediately before and after the month of the intervention were excluded from the savings calculations.

As a result of the various exclusions from the full set of program participants (due to both data cleaning and matched pair cleaning), varying proportions of the total participant population were used to calculate average savings across households in any given month. This implies that the pairs available for a given month represent a statistical sample of the participant population for that month. The participant population also varied over time depending on the take-up of the program. To determine whether the net savings estimated for a given month could be used in calculating the global average savings of the particular program, monthly savings estimates were tested using a two-tailed paired t-test. The global mean saving (and standard deviation) were then derived from the significant monthly savings estimates using a weighted analysis of variance calculation.

The paired t-test evaluates the null hypothesis (H_0) that the difference in the two groups of observations is the same. The alternative hypothesis (H_A) is that the opposite is true; that is, that the groups are not equal. With a confidence of 95%, the null hypothesis can be rejected if the result from the t-test (the so-called p-value) is below 0.05. The null hypothesis (H_0) for our case can be formulated as follows:

> The mean difference in water consumption between (actual) controls and (future) participants before program implementation, and the mean difference in water consumption between (extrapolated) controls and (actual) participants, are equal.

If the null hypothesis could be rejected, the difference between the groups was statistically significant at the 95% confidence level. This meant that the net savings estimate for the month was valid and could be used in the calculation of the global average monthly savings of the particular program.

The paired t-test described above was used to evaluate average monthly savings across households. In order to obtain a global savings and confidence interval across time as well as households, a weighted analysis of variance was necessary to account for changing variance over the period of analysis. Changing variance occurs due to the different number of observations in each month as the participant population changes. The global weighted average monthly savings (global monthly mean) was calculated by taking the sum product of monthly savings observations and the number of observations, and dividing it by the total number of monthly observations:

$$Globalmonthlymean = \frac{\sum_{i=1}^{N}\left[(Monthlyaverage)_i \cdot (Monthsparticipation)_i\right]}{\sum_{i=1}^{N}(Monthsparticipation)_i} \qquad 18$$

where *i* is the household index.

The number of monthly observations for each participant varied depending on the length of participation, so the global monthly mean was weighted according to length of participation. The global monthly mean (expressed in L/hh/d) was multiplied by 365 and converted to kilolitres (kL) to obtain the global weighted annual mean (global annual mean) in kL/hh/year.

The global weighted monthly standard deviation (global monthly SD) was calculated by taking the square root sum of monthly variances for all participants across all months of participation:

$$Global\,monthly\,S.D. = \sqrt{\frac{\sum_{i=1}^{N}\left\{\left[(Monthly\,average)_i - Global\,montly\,mean\right]^2 \cdot (Months\,participation)_i\right\}}{\sum_{i=-1}^{N}(Months\,participation)_i - 1}} \quad 19$$

where N is the total number of participants (or matched pairs).

The denominator of the equation is the degrees of freedom of the calculation.

The global monthly SD was then used to calculate the global monthly standard error (global monthly SE), which is given as the global SD divided by the square root of the number of observations, N (total number of participant households):

$$Global\,monthly\,S.E. = \frac{Global\,monthly\,S.D.}{\sqrt{N}} \quad 20$$

The global monthly SE was multiplied by 365 to get the global annual SE.

Confidence intervals for the global mean savings could then be calculated using the 95% confidence interval t-value for the sample, based on the degrees of freedom described above. The confidence interval for the global weighted mean is expressed:

$$-(t-value)\times(Global\ monthly\ S.E.) \leq (Global\ montly\ mean) \leq (t-value)\times(Global\ monthly\ S.E.) \quad 21$$

Results

The global weighted annual mean savings and associated confidence interval for each program are presented in Table 5.6. Figures in italics indicate that the net savings are not statistically significant (that is, the variability observed in the savings estimates was too great to declare with 95% certainty that the global monthly means were not attributable to pure chance).

Table 5.6: Water savings estimates from the MPMC analyses

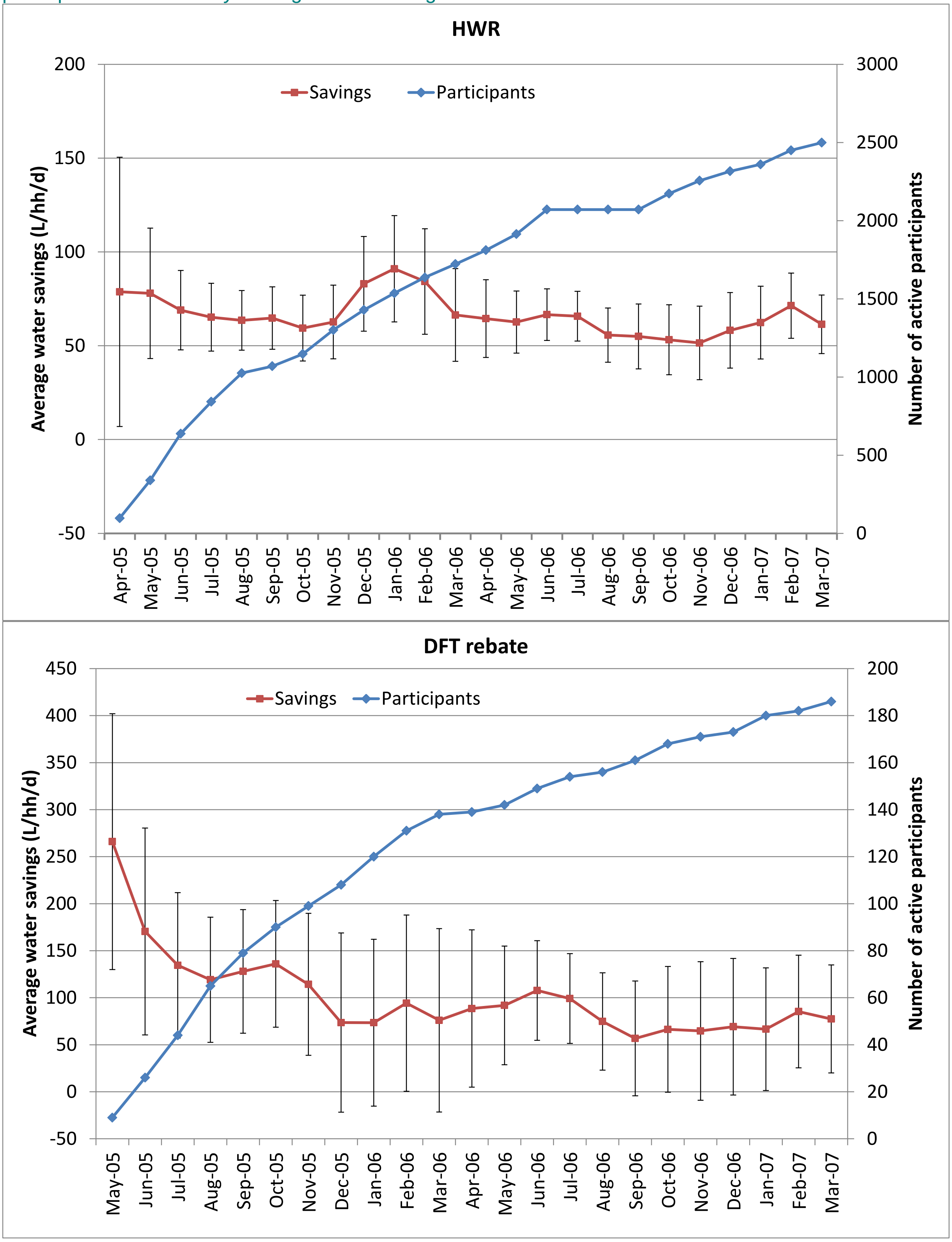
Subprogram	Total sample of participants	Total number of data points[a]	Savings (kL/hh/year) *Average*	*Confidence interval*
WSH retrofit	2 581	41 390	23.6	± 4.3
DFT rebate[b]	190	3 040	31.5	± 16.4

a The number of all monthly savings from all households.
b Includes HWR.

The DFT program (which participants must enter in conjunction with the HWR program) reduced residential household water use by 31.5 ± 16.4 kL/hh/yr. Participants in the HWR retrofit who did not opt for the DFT rebate produced savings of 23.6 ± 4.3 kL/hh/yr.[2]

[2] HWR refers to participants who did *not* participate in Dual Flush.

Time series plots of water savings by month are presented in Figure 5.2.. Both the HWR and the DFT rebate exhibit fairly consistent savings over time, which would be expected given the structural component of the programs. The initial decline in savings from the DFT rebate is more an artefact of the sample than the savings achieved. Evidently, the earliest adopters reduced their demand more than the broader sample. Figure 5.2 Time series plots of program participation and monthly average water savings for the WSH retrofit and DFT rebate



5.8.3 Covariate regression

The second method used in the case study was the covariate regression modelling technique described in Section 5.4.3. Since the analysis is applied at an aggregate level and relies solely on changes in consumption over time to detect savings, it is considered less powerful than the MPMC method. Moreover, the method has not been widely tested. However, it offers a simpler alternative to the MPMC method that can be implemented using standard statistical packages with minimal expertise.[3] Hence, this case study is effectively a demonstration of the potential of the covariate regression technique, using the MPMC technique as a benchmark against which to compare the outputs from the covariate regression analysis.

Selection of a constant data domain

In the covariate regression technique, household consumption records are aggregated by subprogram or control group to generate time series of average household demand for each group. A critical preparatory step in this process is to remove households that do not have a complete consumption record over the period to be analysed. This ensures that the aggregate consumption figures are derived from a constant data domain so that modelled relationships between the participant and control groups remain constant. If the domain is allowed to vary (that is, if the number of control or participant households used to calculate aggregate consumption is allowed to change with time), any relationship drawn between groups cannot be assumed to remain constant. The model specification is thus fundamentally flawed and the water savings obtained from the program take-up variable would be likely to be incorrect.

Binned CMDD for the control and participant groups was first examined in order to select a timeframe in which most households had a complete consumption data record. Figure 5.5 shows the number of households with a consumption figure in a given month for the control and HWR groups, along with the associated average household consumption time series. A large majority of the households in the samples had consumption data between October 1993 and March 2007. Outside that time window, the number of households with consumption data dropped dramatically. Similar results were found for the other subprograms. Therefore, this time window was used to define the temporal data domain for all covariate regression analyses.

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[3] Assuming that the CMDD used in the analysis is already binned to a monthly time step.

Figure 5.5: Number of control and participant (HWR) households with consumption data for a given month plotted with average household consumption for control and HWR participant groups

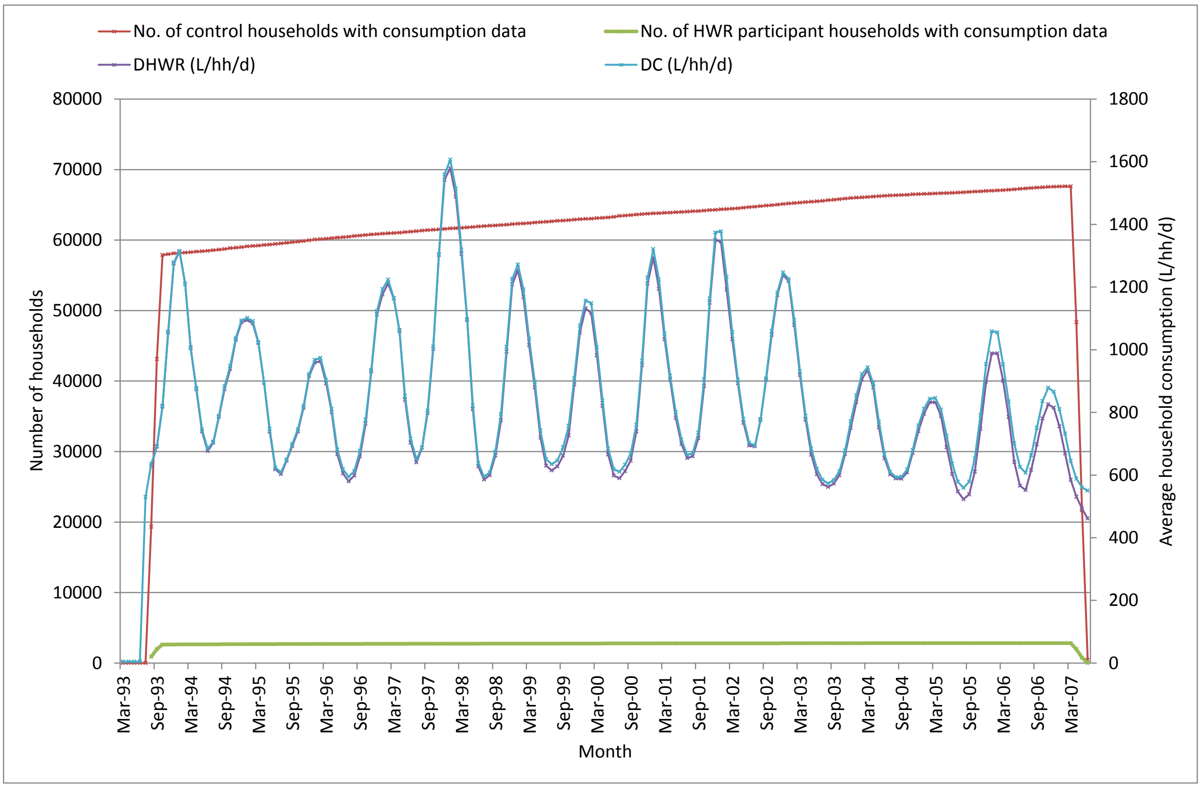


Figure 5.5 also shows how the number of households with data gradually increased with time due to the entry of new households. Because the new households did not have full records, they had to be removed from the dataset to ensure that the domain of the data used to calculate the aggregate consumption remained constant.

Model specification

As explained in Section 5.4.3, covariate regression models are formulated with a small number of variables. This is particularly beneficial when analysing shorter time series of monthly demand, since it limits the number of variables that can be used without compromising the degrees of freedom and thereby the power of the model. Average water consumption of the subprogram participant group of interest (that is, the response variable) was the variable to be estimated. Most of the response variability is explained by the average water demand of the control group, which should account for seasonal variability, a portion of demand reduction associated with the implementation of water restrictions and a variety of other external influences.

The inclusion of additional dummy variable/s for water restrictions was designed to account for the fact that participant and control households may respond differently to water restrictions and consequently reduce their water consumption by different amounts. Similarly, a dummy variable indicating a major change in the pricing rate structure was used to account for the fact that participant and control households may respond differently to changes in price rate structure.

Finally, if the variable indicating the percentage of households participating in a given subprogram was found to be significant, the savings could be directly estimated from the associated regression coefficient. The specifications of variables in the key categories are discussed below.

Water consumption

Binned CMDD from the households retained in the data domain selection process were aggregated into control and participant groups to generate time series of average monthly demand, which were to be used as the response and explanatory variables in the regression modelling process. The average demand variables were named as follows:

- DC = control group demand
- DDF = DFT group demand
- HWR = HWR group demand.

Water restrictions

Between November 2002 and March 2007, there had been seven different forms of water restrictions in force. In November 2005, a new regime was introduced that changed the definition of each of the stages of restrictions. The timings of the various forms of restrictions are summarised in Table 5.7. Because monthly CMDD was used in the analyses, restrictions dates were rounded to the nearest month in subsequent analyses.

Table 5.7: Water restrictions in place over analysis period

Water restriction	*Implementation date*	*Acronym used in regression models*
Voluntary Restrictions	15/11/2002	WR0
Stage 1 Restrictions	16/12/2002	WR1
Stage 2 Restrictions	29/04/2003	WR2
Stage 3 Restrictions	1/10/2003	WR3
Stage 2 Restrictions	1/03/2004	WR2
Stage 3 Restrictions	1/09/2004	WR3
Stage 2 Restrictions	1/03/2005	WR2
Stage 1 Water Conservation Measures (trial for Permanent Water Conservation Measures)	1/11/2005	WR5
Permanent Water Conservation Measures	31/03/2006	WR5
Stage 2 Restrictions (new Temporary Water Restrictions Scheme introduced—this Stage 2 is equivalent to the old Stage 3)	1/11/2006	WR3
Stage 3 Restrictions (this Stage 3 is equivalent to the old Stage 4)	16/12/2006	WR4

Three separate covariate models were constructed to predict water savings from each program. The first model type did not include any water restrictions variables, which effectively makes the assumption that control and participant households generally respond to water restrictions in the same manner. This model was deemed parsimonious, and was essentially used as a basis for comparison with the models incorporating water restrictions variables.

The second model type used separate dummy variables for each distinct stage of water restrictions. It should be noted that stages of water restrictions that had equivalent rules were defined using the same dummy variable. For example, Stage 3 Restrictions (old) and Stage 2 Restrictions (new) were defined using the variable WR3, while Stage 1 Water Conservation Measures and Permanent Water Conservation Measures were defined using the variable WR5. The main limitation with using separate dummy variables for each distinct stage of water restrictions was the reduction in model parsimony. It also made it more possible for potentially superfluous variables with random correlations to water demand to be included in the model.

The third type of restrictions specification lumped similar (but not necessarily identical) stages of water restrictions into single variables. This specification was based on interpretation of the water restrictions criteria—specifically, the watering hours associated with various activities. Voluntary water restrictions were perceived to have little or no influence on demand. As a result, that stage of water restrictions was not used in any of the lumped variables. Stage 3 Restrictions (old), Stage 2 Restrictions (new) and Stage 3 Restrictions (new) were perceived to be the most stringent stages of water restrictions. As a result, a single lumped dummy variable (WR34) was created using those stages of water restrictions. Stage 1 Restrictions (old), Stage 2 Restrictions (old), Stage 1 Water Conservation Measures (new) and Permanent Water Conservation Measures were perceived to be less stringent than the aforementioned stages of water restrictions. However, they were still assumed to influence water demand. As a result, those stages were also lumped together in a single dummy variable (WR125). Lumping similar stages of water restrictions into fewer variables was deemed to increase model parsimony, thereby leading to more robust models that are also easier to interpret.

Following testing of the three types of specifications, the regression models using the lumped water restriction dummy variables were deemed to be the most valid. Not only did the models use fewer variables than the regression models based upon separate dummy variables, in most cases they preferentially entered the more stringent water restrictions variables over the less stringent, suggesting that the modelled effects were not sporadic. Furthermore, they were deemed more valid than the models using no water restrictions variables, factoring the difference in response to water restrictions between control and participant households. Without water restrictions variable/s, the effects associated with the water restrictions could potentially be incorrectly apportioned to the cumulative rebate count, resulting in model bias.

Price variable

As well as yearly variability in fixed and volumetric usage charges, there had been a number of changes to the tariff structure and intra-marginal rates. It was assumed that the control and participant households may have responded differently to changes in the tariff structure. As a result, a dummy variable was used to reflect the major change in rate structure, which occurred on 1 August 2004.

In the majority of cases, the rate structure change variable was not found to be significant. However, when it was found to be significant, it adversely affected the water restrictions and demand-management program cumulative count variables. This was due to a potentially large correlation between the variables. Previous analyses of Melbourne CMDD (Fyfe et al. 2009abc) indicated that changes in the price tariff structure generally had a much smaller influence on water consumption in covariate models when compared to water restriction and demand-management program variables. As a result, the price structure variable was not included in the final regression models.

Program take-up variables

The program take-up variables were specified as a cumulative percentage count of households participating in the subprogram, relative to the total number of participants. This meant that the variable coefficients derived in the models would directly reflect the savings associated with the subprograms. To ensure that the coefficient derived would have sufficient significant figures to report on, the variables were expressed as a percentage figure (as opposed to a decimal fraction). The coding of the program take-up variables used in the models was:

- CDF = DFT rebate take-up
- CHWR = HWR retrofit take-up.

Results

Stepwise regression analysis produced the final model equations presented in Table 5.8. Average control group consumption was the most significant variable in both models, explaining the greatest portion of variability. The cumulative count of participants in each program was typically the second most significant variable, and the water restrictions dummy variables explained much smaller portions of variability.

Table 5.8: Final covariate model equations

Subprogram	*Model equation*	*R^2_{adj}*
HWR retrofit	HWR = –5.84 + 0.992*DC – 0.548*CHWR	0.999
DFT rebate	DDF = –16.4 + 0.984*DC – 0.782*CDF + 21.2*WR34	0.989

Estimates of savings from the various rebate programs were derived from the regression coefficients associated with the cumulative take-up variable in the final covariate models. The regression coefficients (and associated 95% confidence intervals) need simply to be multiplied by 100 to obtain the average daily household water savings associated with a given program. They were then multiplied by 0.365 (365 days per year divided by 1000 L per kL) to calculate annual savings in kL. The water savings estimates derived from the final regression models are presented in Table 5.9. Note that the method for deriving confidence intervals is based on the regression analysis alone. For a true account of the uncertainty of the savings estimates, the standard error of the aggregated participant demand should be incorporated into the calculation.

Table 5.9: Water savings estimates from with the final covariate regression models

	Average water savings (kL/hh/year)	
Subprogram	*Average*	*Confidence interval*
WSH retrofit	20.1	± 1.8
DFT rebate	28.5	± 5.8

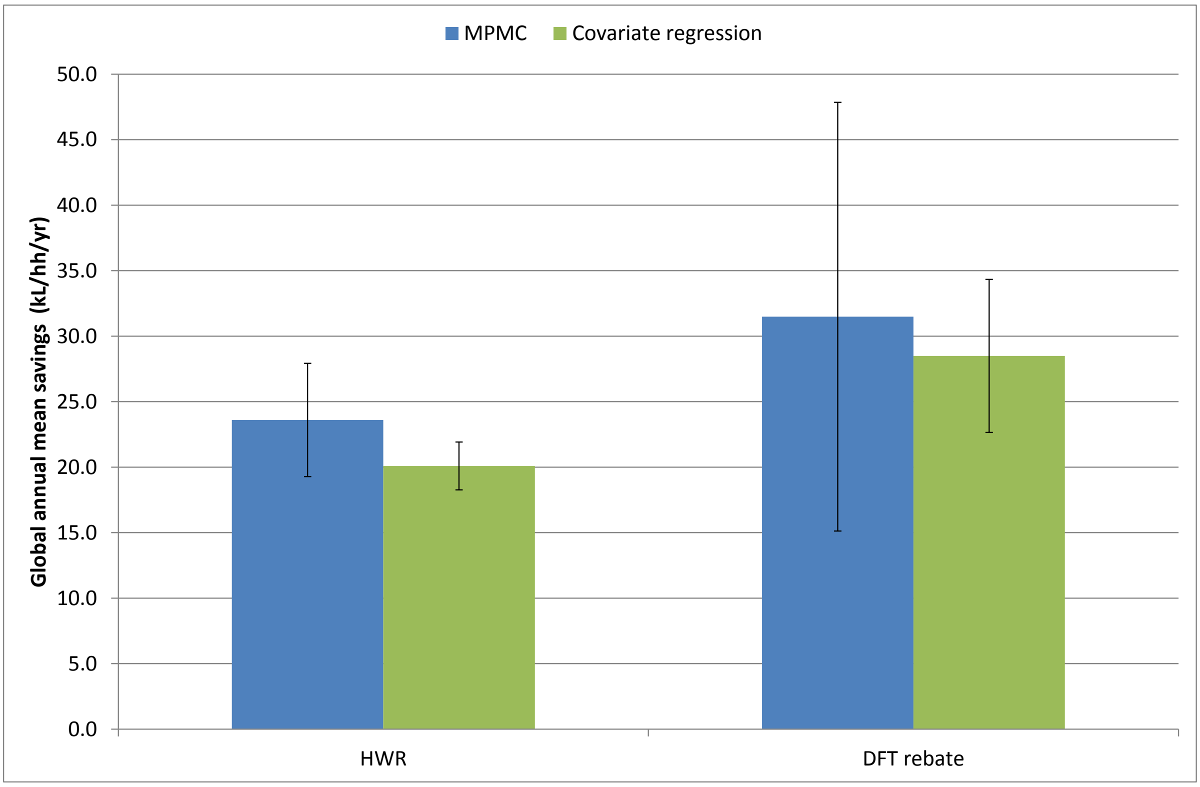
5.8.4 Comparison of savings estimates from MPMC and covariate regression

The water savings associated with demand-management programs derived using covariate regression models are compared with the MPMC results in Figure 5.6. In general, the savings derived using the two approaches were consistent with one another, as implied by the overlap between the confidence intervals. It is important to emphasise again that the confidence intervals on the covariate regression results do not express the full extent of uncertainty of the analysis. Hence, while the confidence intervals on the covariate regression estimates are narrower than the MPMC confidence intervals, they should not be interpreted as the covariate regression being a more precise method. Until a method of expressing the true uncertainty of the covariate regression technique is devised, the method should be viewed as less accurate than the MPMC approach.

Water savings estimates derived using the covariate approach were lower for both of the programs investigated, implying that the covariate approach produced more conservative results. It could be inferred that this stems from the fact that the MPMC analysis does not explicitly account for the effect of water restrictions, but relies on the matching process to identify controls that exhibit responses to restrictions similar to their participant counterparts'. However, inspection of the covariate regression coefficients for water restrictions variables reveals that participants actually reduced their water usage less than the broader population in response to restrictions. This suggests that savings would be underestimated by the MPMC analyses if the controls identified by the pair matching algorithm did not respond to restrictions in a similar fashion to participants. Hence, it is suggested that the covariate regression results are consistently lower because savings in the covariate analysis are calculated from aggregate consumption figures using a much broader control group. By calculating savings on a household basis, the MPMC approach works at a finer resolution and is thus capable of picking up savings that are otherwise lost in aggregation.

Another limitation of the covariate regression technique is its inability to generate a time series of savings estimates. Because the method estimates savings based on change in aggregate demand over time, it can only produce a single average savings estimate, which means there is no ability to assess the consistency of savings over time or savings seasonality. So, while covariate regression offers a simpler means of evaluating water savings from a demand-management program, MPMC remains the more powerful method of analysing savings in the absence of detailed data on household characteristics.

Figure 5.6: Comparison of MPMC and covariate regression water savings estimates



5.8.5 Summary

The MPMC and covariate regression analyses produced statistically significant estimates for the HWR program and the DFT rebate. MPMC produced robust savings estimates at a high resolution (household-by-household, month-to-month) with minimal data requirements. However, the method requires substantial computational effort and a high degree of expertise in programming and database interrogation to make it a manageable, automated process. The covariate regression models produced very similar results to the MPMC analyses, albeit consistently lower, most likely due to the coarseness of the technique. The method requires further development so that the uncertainty of savings estimates is properly accounted for in the confidence intervals. However, it appears to have the potential to provide a simpler alternative to the MPMC approach (and other regression techniques) that produces comparable savings estimates to the MPMC benchmark.

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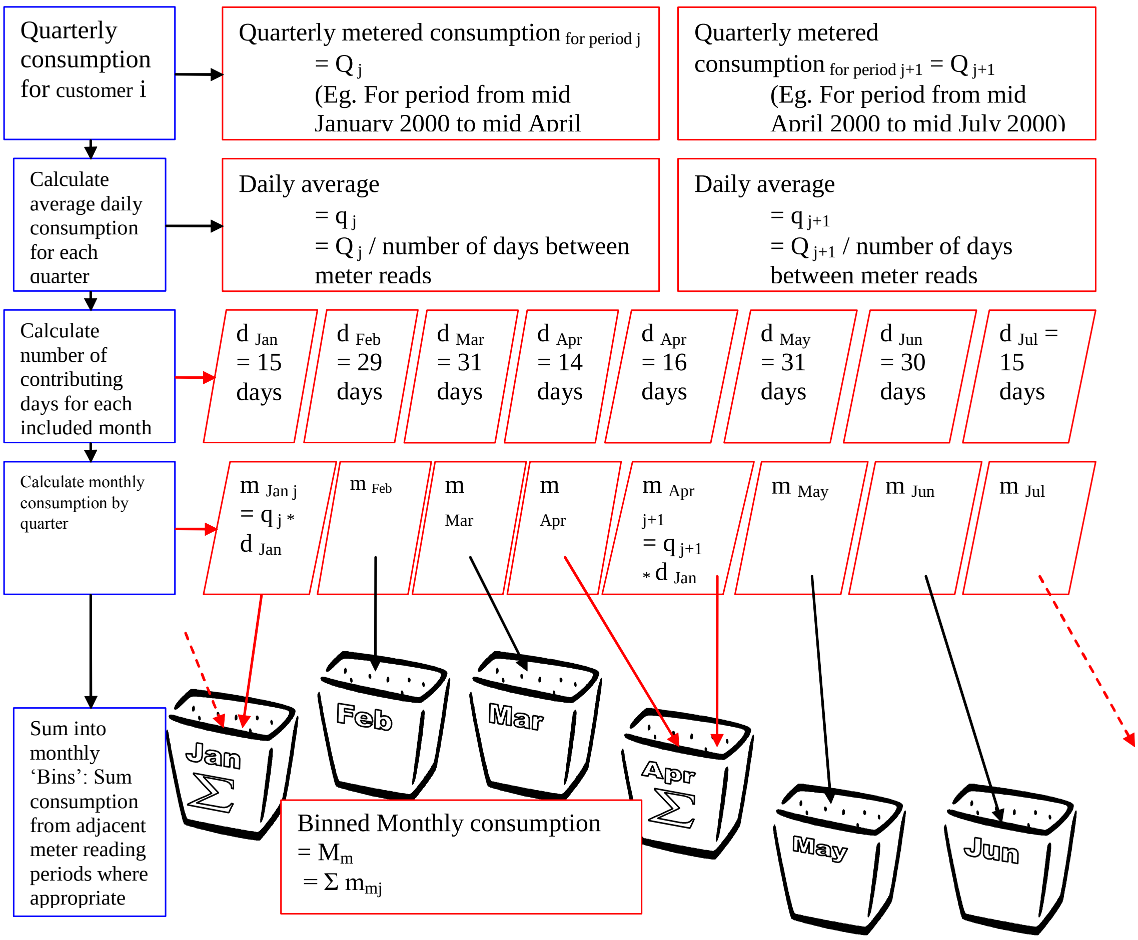
Appendix 5A: Data binning

Individual customer demand data is typically only available at relatively infrequent intervals. Furthermore, customer meter data is typically recorded on different days in different districts. These potential limitations have given rise to the need for data ‘binning’. Binning involves apportioning periodically recorded demand into shorter, consistent time periods, which aids in the direct comparison of usage profiles of individual customers and in data aggregation. An illustration of the binning process is presented in Figure 5A.1.

Figure 5A.1: Illustration of apportioning demand into monthly bins of time



Generally, quarterly demand data is converted to monthly demands, as shown in Figure 5A.2. Average daily demands are first derived for each quarter by dividing total quarterly demand by the number of days in the quarter:

$$C_{d,i} = \frac{C_{q,i}}{d_{q,i} - d_{q,i-1}} \qquad 22$$

where

$C_{d,i}$ = the average daily consumption for the ith quarter (kL/d)

$C_{q,i}$ = the total consumption for the ith quarter (kL)

$d_{q,i}$ = the last day of the ith quarter (expressed as a Julian day)

$d_{q,i-1}$ = the last day of the (i-1)th quarter (expressed as a Julian day).

Two equations are then used to calculate monthly demand from quarterly meter reads, depending on where the particular month lies in relation to the quarterly meter reads. If all days for a given month occur in a single quarterly interval, the following equation is used:

$$C_{m,j} = \left(d_{m,j} - d_{m,j-1}\right) \cdot C_{d,i} \qquad 23$$

where

$C_{m,j}$ = the binned monthly consumption for the jth month (kL)

$d_{m,j}$ = the last day of the jth month (expressed as a Julian day)

$d_{m,j-1}$ = the last day of the (j-1)th month (expressed as a Julian day).

Alternatively, if days for a given month occur in two quarterly intervals, the daily demand from both quarters is used:

$$C_{m,j+1} = \left(d_{m,j+1} - d_{q,i}\right) \cdot C_{d,i+1} + \left(d_{q,i} - d_{m,j}\right) \cdot C_{d,i} \qquad 24$$

where

$C_{m,j+1}$ = the binned monthly consumption for the (j+1)th month (kL)

$d_{m,j+1}$ = the last day of the (j+1)th month (expressed as a Julian day)

$C_{d,i+1}$ = the average daily consumption for the (i+1)th quarter (kL/d).

There are a number of limitations associated with the data binning process. The technique assumes that daily demand is constant over the given meter-read period, which is often not the case (Moglia et al. 2009). Furthermore, while binning helps to improve the seasonality profile of customer metered demand (more so after aggregation), there is a 'smearing' effect (an artefact of subdividing quarterly data) whereby demand for any given month is in part determined by demand in the previous and following months. When using binned data in a time series regression, it may be necessary to use (demand) lag and/or lead terms as explanatory variables to account for this.

Figure 5A.2: Division of quarterly consumption data into monthly consumption data via the binning process